WHITE PAPER

OFFICE OF MANAGEMENT AND BUDGET

CLIMATE FINANCIAL RISK:

THE FEDERAL GOVERNMENT'S BUDGET EXPOSURE TO FINANCIAL RISK DUE TO CLIMATE CHANGE

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Introduction

The effects of human-caused climate change are already far-reaching and worsening across the United States (U.S.). Across all regions of the Nation, people are experiencing warming temperatures and longer-lasting heatwaves (Jay et al., 2023). Over much of the U.S., nighttime temperatures and winter temperatures have warmed more rapidly than daytime and summer temperatures. Many other extremes, including heavy precipitation, drought, flooding, wildfire, and hurricanes, are becoming more frequent and/or severe, with cascading effects in every part of the country.

To help address the threat that climate change poses to the economy, President Biden signed E.O. 14030 “Climate-Related Financial Risk” on May 20, 2021. Section 6(b) of the E.O. 14030 directs “[t]he Director of Office of Management and Budget and the Chair of the Council of Economic Advisers, in consultation with the Director of the National Economic Council, the National Climate Advisor, and the heads of other agencies as appropriate, [to] develop and publish annually, within the President’s Budget, an assessment of the Federal Government’s climate risk exposure.” This report supplements materials within the President’s Budget as required by Section 6(b) of the E.O. 14030.

One of the most direct ways that people experience climate change is through changes in weather-related extreme events. Harmful impacts from more frequent and severe extreme weather events are increasing across the country—including increases in heat-related illnesses and death, costlier storm damages, longer droughts that reduce agricultural productivity and strain water systems, and larger, more severe wildfires that threaten homes and degrade air quality (Jay et al., 2023).

The U.S. has sustained 376 weather and climate disasters between 1980 and 2023 each with overall damages and costs of at least $1 billion (including CPI adjustment to 2023) (NOAA, 2024). The total cost of these 376 events exceeds $2.660 trillion. In 2023 alone, there were 28 confirmed weather/climate disaster events in the U.S. with losses exceeding $1 billion each—the highest on record. The 1980–2022 annual average is 8.5 billion-dollar events; the annual average for the most recent 5 years (2019–2023) is 20.4 billion-dollar events (Smith, 2024).

Climate change will affect federal spending and revenue substantially (Dolan et al., 2023). Damages from extreme weather events are expected to increase significantly in the coming decades because of the effects of climate change, spurring increases in federal relief and recovery requests. As broad economic damages from climate change grow, so does the impact of the climate crisis on the Federal Budget. For example, crop insurance, coastal flooding, health insurance, and wildfires are expected to substantially increase the annual spending of the government. The Federal Government's budget is directly and substantially at risk from expected lost revenues and increasing expenditures due to climate change damages in coming decades, such as increasing costs from physical damages to our Nation's infrastructure and healthcare expenditures, the instability of certain subsidized insurance programs, growing costs of disaster relief, and accelerating instability that threatens global security. Given these demands, achieving sustainable public budgets in a changing climate is expected to require additional revenues or other expenditure reductions (Hsiang et al., 2023).

This white paper supports the Federal Budget Exposure to Climate Risk Analytical Perspectives (AP) chapter of the 2025 President's Budget and provides additional technical discussion and presentation of methods employed in the assessments and program highlights described in the AP chapter. Additionally, this white paper complements the analysis directed by Section 6(a) of E.O. 14030, which requires "the Director of OMB, in consultation with the Secretary of the Treasury, the Chair of the Council of Economic Advisers, the Director of the National Economic Council, and the National Climate Advisor, [to] identify the primary sources of Federal climate-related financial risk exposure and develop methodologies to quantify climate risk within the economic assumptions and the long-term budget projections of the President's Budget." The work directed by Section 6(a) takes a broad, macroeconomic view of the impact of climate risk on the economic assumptions used within the President's Budget, which includes gross domestic product (GDP), and the long-term budget outlook.

Although the long-term budget projections are not directly incorporated in this report, the impact of climate change on macroeconomic trajectories in turn impacts the projections of Federal revenue and expenditures in the President's Budget. The "Analysis of Federal Climate Financial Risk Exposure" *Analytical Perspectives* (AP) chapter of the President's Budget assesses the magnitude of this indirect, macroeconomic channel through which climate risk affects the long-term fiscal outlook. Therefore, together the analyses relating to Section 6(a) and Section 6(b) of E.O. 14030 illustrate the multi-faceted impact of climate change on the Federal Budget.

This white paper provides a demonstration of the various approaches currently being employed to assess climate risk to agency programs, facilities, and services, including two analyses that provide detailed projections of quantified financial risks to agency programs. Additionally, this paper highlights new risk and assessment analytical capabilities recently published along with the Fifth National Climate Assessment (NCA5). As such, this paper is organized into a set of themes that relate to each assessment, and is organized under: (1) Disaster Preparedness and Response, (2) Risks to Long-Term Infrastructure, (3) Social Safety Net and Human Health, (4) National Security, and (5) a final section that highlights new climate risk assessment capabilities and decision support tools.

Background

The "Federal Budget's exposure to climate financial risk" is an umbrella term that captures how climate change can impact Federal expenditures and revenue. This paper highlights existing and proposed work that investigates a few of the specific areas where the Federal Government is vulnerable to climate-related financial risk. Climate-related financial risk[1] includes both the physical risks of climate change—resulting from changes in extreme weather events, such as wildfires, storms, and floods—and transition risks (and associated benefits) that result shifting to a lower-carbon economy. The AP chapter and this white paper focus on physical risks of climate change to the Federal government. The extent to which Federal expenditures are impacted by

[1] Throughout this white paper, the term 'climate-related financial risk' refers to the budgetary risks borne by the Federal Government through the administration of programs and policies. Climate change also poses financial risks for individuals and firms, though these risks are not considered in this paper.

climate change depends on the nature of the Federal program or type of Federal funding being committed. Federal funding generally falls into the categories of discretionary or mandatory spending.[2]

- Mandatory: money that is provided by an authorizing law, which allocates money each year or for a set of years to be spent on specified activities or goods. This funding may have a set amount for a specified time period or provide "such sums as necessary" for the operation of a Federal program.
- Discretionary: money that is provided in annual appropriations. Supplemental funding may occur outside of annual appropriations when there is an urgent need for funding, such as the series of supplemental appropriations related to the pandemic or additional assistance after an extreme weather event.

The Federal Government's direct support can take multiple forms including direct payments, loans, and insurance. The Federal Government offers direct loans and loan guarantees to support a wide range of activities including home ownership, higher education, small business, farming, energy, infrastructure investment, and exports. Through its insurance programs, the Federal Government insures deposits at depository institutions, guarantees private-sector defined-benefit pensions, and insures against some other risks such as flood and terrorism. More information on Federal credit and insurance programs is available in the *Analytical Perspectives* Chapter "Credit and Insurance" of the President's Budget.

Both mandatory and discretionary funding in the Budget can be impacted by climate change. In some cases, programs, like Medicare, may experience higher outlays (spending) since the program's funding is described as "such sums as necessary," which do not cap the outlay amounts. However, climate change may not always result in higher outlays. For example, Federal activities that have funding amounts set in statute may not, in the short run, have expenditures exceed the designated statutory amount. Instead, these programs may have to serve a smaller number of recipients or reduce the benefits per recipient when faced with increased demand for the program. This may apply to appropriated programs if funding levels do not fully adjust to reflect the changes in extreme weather or conditions such as drought intensity and frequency. In the long-run, if Congress increases funding to Federal activities more vulnerable to climate change, these decisions may lead to trade-offs with other fiscal goals, and may result in reductions to other Federal programs or increased borrowing. These unknown future tradeoffs highlight the complexities of examining the Federal Budget's exposure to climate risks.

1. Disaster Preparedness and Response

Climate change is already affecting people in the U.S., including through the effects of climate-related disasters. Human activities are affecting climate system processes in ways that alter the intensity, frequency, and duration of many weather and climate-related extremes, including extreme heat, extreme precipitation and flooding, agricultural and hydrological drought, and

[2] For a comprehensive overview of the structure and processes of the Federal Budget, readers can refer to the Analytical Perspectives Chapter "Budget Concepts" of the President's Budget.

wildfire (Leung et al., 2023). Disasters are now coming more frequently and causing more damage. In the 1980s, the country averaged one (inflation-adjusted) billion-dollar weather disaster every four months. Now it averages one every three weeks (NOAA, 2022). However, disaster risk in a complex society such as the U.S. is never determined simply by extreme weather events. It also depends strongly on exposure (i.e., who or what lies in the path of different hazards) and vulnerability (i.e., their ability to cope with those hazards) (Marvel et al., 2023). Climate change interacts with existing social, political, and economic structures— for example, increases in property values and increased development in hazard hotspots have also contributed to the increase in billion-dollar disasters—and exacerbates existing inequalities.

Climate change is increasing the chances of multiple climate hazards occurring simultaneously or consecutively across the U.S. and its territories. Such interactions between multiple hazards across space or time, known as compound events, exacerbate the societal and ecosystem impacts of individual hazards and hinder the ability of communities, particularly frontline communities, to respond and cope. As an example, the compound effects of heat, drought, and wildfires can stress communities and ecosystems and cause significant economic damages. When combined, compound events have greater impacts than isolated hazards on ecosystems, water resources, public health, energy infrastructure, transportation, food systems, and interconnected societal networks, often straining disaster response (Singh et al., 2023). Therefore, infrastructure design, planning, governance, adaptive land and water management, and disaster preparedness for compound events are critical for building resilient systems. U.S. Government agencies face a range of financial risks associated with climate-related disasters to their respective portfolios. This section provides details on two risk assessments described in the AP chapter of the 2025 Budget: (1) an overview of the climate financial risk associated with the U.S. Department of Agriculture (USDA)'s Livestock Forage Disaster Program, and (2) an update on projected wildland fire suppression costs due to climate change impacts on lands managed by the USDA Forest Service and the bureaus of the U.S. Department of the Interior (DOI).

U.S. Department of Agriculture: The Climate Financial Risk of the Livestock Forage Disaster Program

Introduction

The agricultural sector is particularly vulnerable to the impacts of climate change, as crop yields, forage availability, and farm profits depend on evolving climatic conditions (Hsiang et al., 2017; Malikov et al., 2020). As noted in the AP chapter of the 2025 budget, the Federal Government administers a variety of programs to support climate change resilience and climate risk mitigation within the agricultural sector (Baldwin et al., 2023). Several of these programs aim specifically at mitigating risk within the livestock sector (MacLachlan et al., 2018). This assessment focuses on one of these programs, the USDA Farm Service Agency's (USDA-FSA) Livestock Forage Disaster Program (LFP), which provides payments to livestock producers impacted by drought or wildfire (Hrozencik et al., 2024).[3] The LFP, and other Federal programs like it, may constitute a financial climate risk for the Federal Government, as projections of climate in the U.S. suggest

[3] LFP payments are only available to cover wildfire-related grazing losses occurring on Federally managed land.

that drought conditions may become more frequent and intense for many regions in the future (Lehner et al., 2017; Leng & Hall, 2019; Zhao & Dai, 2017). Specifically, this assessment presents analyses modeling the financial climate risk for the Federal Government's budget associated with the program under different emissions scenarios.

The LFP, which was initially established by the 2008 Farm Bill, aim to compensate livestock producers experiencing losses in forage due to drought or wildfire (MacLachlan et al., 2018). LFP payments cover livestock feed costs on a per-animal basis for eligible expected losses due to drought. USDA-FSA administers the LFP and annually sets species-specific per-animal payment rates, as well as county-level eligible grazing periods. LFP payment rates are set to reflect feed costs and generally aim to cover 60 percent of the per-animal feed expenditures. To be eligible for LFP payments, the county within which a livestock producer operates must experience drought conditions exceeding a specified threshold during the county's eligible grazing period.[4] County-level drought conditions are classified weekly by the U.S. Drought Monitor (USDM), which designates 5 levels of increasing drought severity ranging from `D0: abnormally dry' to `D4: exceptional drought.' See Table 1 for a full schedule of LFP eligibility criteria and months of LFP payments.

TABLE 1: ELIGIBILITY CRITERIA FOR THE LIVESTOCK FORAGE DISASTER PROGRAM MONTHLY PAYMENTS

Months of LFP Payments	Eligibility Criteria
1	Eight or more weeks of continuous severe drought (D2) during the county eligible grazing period
3	If at any time during the county eligible grazing period extreme drought (D3)
4	Four or more weeks (not necessarily continuous) of extreme drought (D3) during the county eligible grazing period OR At least one week of exceptional drought (D4) during the county eligible grazing period
5	Four or more weeks (not necessarily continuous) of exceptional drought (D4) during the county eligible grazing period

Note: This table presents the eligibility criteria for the USDA's Livestock Forage Disaster Program (LFP) as defined by county-level drought conditions classified by the U.S. Drought Monitor (USDM). Livestock producers become eligible if they are located within a county whose drought conditions, as defined by USDM, meet at least one of the eligibility criteria. USDM releases geospatially explicit data on a weekly basis classifying drought conditions for all U.S. States and Territories. These data are aggregated at the county level and livestock producers with a given county become eligible if any regions of their county of operation meet the LFP eligibility criteria. Eligibility criteria are not hierarchical. For example, a county does not necessarily need to meet the criteria for one month of LFP payments to become eligible for three months of LFP payments. In some rare occasions, livestock producers may be eligible for two months of LFP payments if they are located within a county that experiences extreme drought during their county's eligible grazing period but their county's eligible grazing period is less than 3 months. This rare occurrence happens most frequently in the northernmost regions of the U.S. where climate conditions constrain the eligible grazing periods to a relatively short period.
Source: USDA, Economic Research Service using data provided by USDA, Farm Service Agency in the Livestock Forage Disaster Program Fact Sheet (USDA-FSA, 2023).

Figure 1 plots annual aggregate LFP payments, in nominal and real values, between 2008 and 2022, highlighting the potential financial climate risk of the program. LFP payments peaked in 2012 at more than \$3 billion (in 2022 dollars) in 2012 when many livestock production regions experienced unprecedented levels of drought severity (Rippey, 2015).[5] Financial climate risks are particularly pertinent to the LFP as eligibility and program payments are a function of drought severity as classified by the U.S. Drought Monitor. If projected increases in drought incidence and severity are realized, then the Federal Government's budgetary expenditures associated with the LFP may also increase substantially.

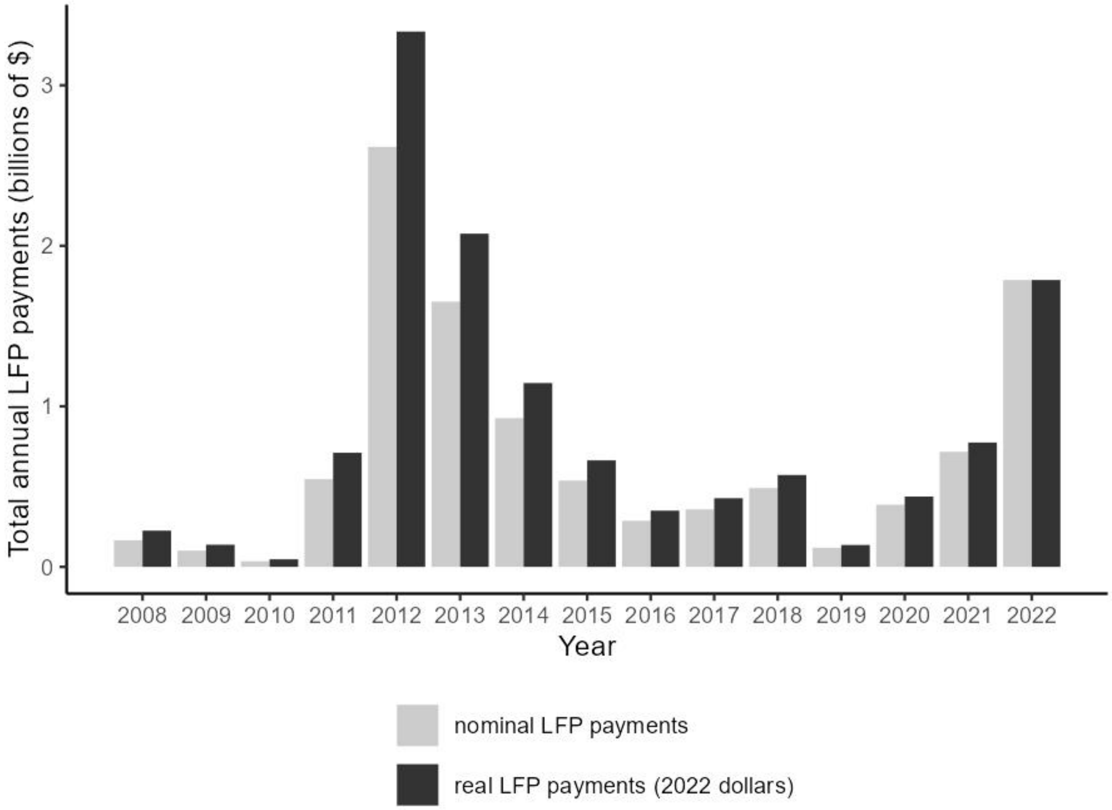
Modeling the financial climate risk of the LFP involves integrating projections of future drought conditions, under differing emissions scenarios, with historical data relating drought severity and duration to LFP payments. Recently, researchers have raised questions regarding classifications of drought in a changing climate, suggesting that classifications of drought based on long-term historical climate conditions, e.g., USDM's classifications, may bias current and future drought

[5] LFP payments to compensate for forage losses arising from the 2012 drought were not sent to producers until 2014 after the LFP was reauthorized by Congress and eligibility criteria were altered to no longer require prior insurance coverage.

assessments toward classifying a region as experiencing drought when more recent climatic data (i.e., where a region is more arid recently compared to historical drought conditions) would suggest conditions do not constitute a drought (Parker et al. 2023). To address these drought classification issues, the LFP financial climate risk model utilizes long-term and medium-term climatic data to construct alternative drought classifications. This analysis presents alternative drought classifications to represent their potential impact on LFP payments, however this assessment or its results do not take a position on broader considerations and consequences of modifying classification of drought.

The LFP was originally authorized through 2011 and imposed a previous risk management purchase requirement for eligibility. The LFP expired in 2011 and was reauthorized with the passage of the 2014 Farm Bill which allowed for retroactive payments to producers experiencing drought-related losses in 2011, 2012, and 2013. Additionally, the 2014 Farm Bill authorization ended the previous risk management purchase requirements for LFP eligibility, opening the program to nearly all U.S. livestock producers regardless of enrollment in private or government insurance programs. Since 2014, annual aggregate program payments have averaged nearly $0.7 billion.

FIGURE 1: TOTAL ANNUAL NOMINAL AND REAL LFP PAYMENTS, 2008-2022



Note: This figure differentiates between nominal and real aggregate annual LFP payments. Nominal aggregate annual LFP payments refer to dollar amount of LFP payments distributed for losses each year. Real aggregate annual payments are these same payments but adjusted for inflation, real annual aggregate LFP payments are presented in 2022 dollars. Aggregate Livestock Forage Disaster Program (LFP) payments include both payments made to producers experiencing forage losses due to drought and wildfire on Federal rangeland leased to producers for grazing. The 2014 Farm Bill changed the eligibility requirements for LFP payments and authorized retroactive payments for producer's impacted by drought conditions in 2012 and 2013 when much of the central U.S. experienced significant drought (Rippey, 2015).
Source: USDA, Economic Research Service using data provided by USDA, Farm Service Agency.

Data and Methods

This assessment on LFP uses historical data to model LFP payments as a function of observed drought conditions and then uses model output to project future LFP payments for a range of emissions scenarios to assess the financial risk of the LFP due to projected climate change. Panel data econometric methods are used to model county-level LFP payments between 2014 and 2022 as a function of USDM drought classifications, which define months of LFP payments (see Table 1), and county-level livestock herd-size. Including county-level herd size in the model is important as LFP payments are made on a per-head basis and county herd size explains a significant amount of the variation in county-level LFP payments. The model estimates a suite of parameters which describe how months of LFP eligibility and livestock herd size impact total annual county-level

LFP payments.[6] These parameters are then used to predict future LFP payments under projected drought conditions. See appendix A for more details on the model.

Projected future drought conditions are derived from an eight-member ensemble of climate projection models across differing emissions scenarios (see “Emissions Scenarios” text box). The ensemble was selected to be consistent with the International Panel on Climate Change (IPCC)’s assessment of the very likely range of Earth's equilibrium climate sensitivity, as assessed by Mahony et al. (2022). The 8-model ensemble includes ACCESS-ESM1.5 (Ziehn et al., 2020), CNRM-ESM2-1 (Séférian et al., 2019), EC-Earth3 (Döscher et al., 2021) , GFDL-ESM4 (Dunne et al., 2020), GISS-E2-1-G (Kelley et al., 2020), MIROC6 (Tatebe et al., 2019), MPI-ESM1.2-HR (Müller et al., 2018), and MRI-ESM2.0 (Yukimoto et al., 2019). Output from these models is downscaled to the 0.25 decimal degree resolution using the National Aeronautics and Space Administration (NASA)’s NEX-GDDP downscaling product and aggregated to a county-month unit of observation (Thrasher et al., 2022). Projections of future precipitation are used to calculate the Standardized Precipitation Index (SPI) and the Standardized Precipitation-Evapotranspiration Index (SPEI). These county-month projections of SPI and SPEI map to different USDM drought classifications. Projections of future USDM classifications are coded as implied months of LFP payment eligibility for each unique combination of county, year, and emissions scenario. See appendix B for more information on drought projections. Finally, these projected months of LFP eligibility and parameters estimated by the econometric model are used to predict county-level LFP payments, deflated to 2022 dollars, using the county-level livestock herd size as of 2022. Figure 2 presents a conceptual diagram of the methods used to model future LFP payments.

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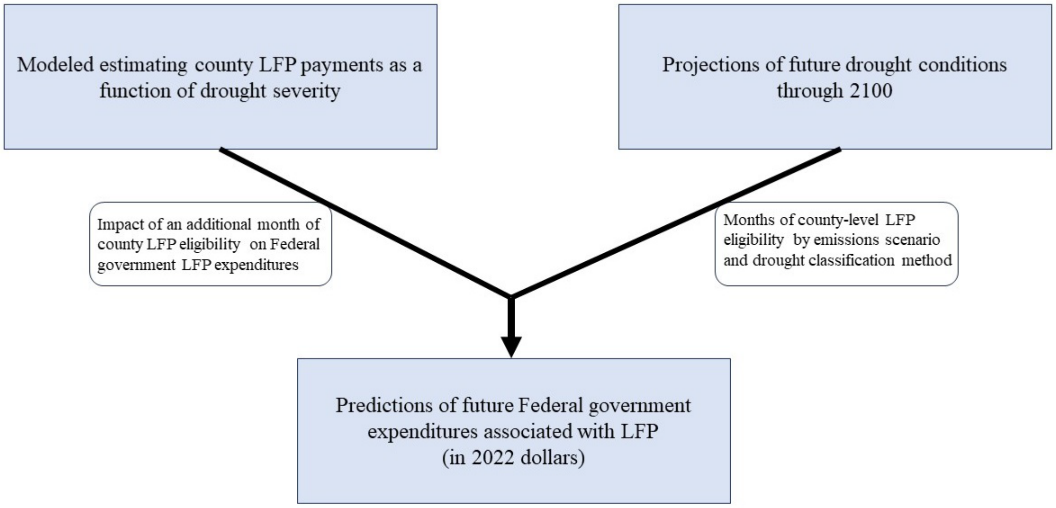
[6] This White Paper uses county-level herd size data on a suite of LFP eligible livestock to estimate how months of LFP eligibility translate into LFP payments. Specifically, this model accounts for time-variant county-level stocks of beef and dairy cattle using data reported by USDA-NASS’ Cattle Survey. Additionally, this analysis includes time-invariant stocks of sheep, goats, and equine species (horses, ponies, mules, donkeys, burros) within a given county as reported in the 2017 Census of Agriculture. Other livestock species are also eligible for LFP payments e.g., deer, elk, bison/buffalo, beefalo, emus, llamas, alpacas, ostriches, and reindeer (see appendix A for more information). Beef cattle, dairy cattle, sheep, goats, and equine species account for more than 99 percent of the total number of LFP eligible livestock species for which county-level data are reported in the Census of Agriculture (e.g., county-level data are not reported for ostriches nor reindeer).

FIGURE 2: CONCEPTUAL DIAGRAM OF METHODOLOGY USED TO PREDICT FUTURE LFP PAYMENTS



Note: This figure conceptually plots the methods used to predict future Federal government expenditures associated with the LFP. Projections of future drought conditions through 2100 are joined output from a model estimating county LFP payments as a function of drought to forecast future LFP payments under differing emissions scenarios and methods for classifying drought.
Source: USDA, Economic Research Service

In addition to projecting LFP payments across a range of emissions scenarios (see Emissions Scenarios text box), this assessment also projects payments considering two alternative approaches to future drought classification. Drought classifications rely on historical climate data to characterize when temperature and precipitation patterns in a given region deviate from long-run averages. Drought detection and classification data products like the USDM rely on 60+ years of climate data to define long-run averages. Using these longer-term climate records in drought assessment implicitly assumes stationarity in climate; i.e., climate from 60+ years ago would be similar to what is expected today (Hoylman et al., 2022). Anthropogenic climate change makes these common stationarity assumptions inappropriate to the extent that climate over the last 60+ years does not resemble current conditions. Rather than rely on stationarity assumptions, climate and weather sciences generally rely on 30 year climate "normals," updated decadally, to describe average climate conditions in a manner that is consistent with a changing climate, i.e., non-stationarity drought classification (Arguez & Vose, 2011). To understand the importance of these stationarity assumptions, this assessment generates projections of LFP payments using both stationarity and non-stationarity definitions of drought.

Several key assumptions are made in this analysis of the financial climate risk of the LFP. The first of these assumptions is that program characteristics (e.g., rules for determining payment rates and eligibility) do not change over time. USDA-FSA annually sets LFP payment rates by livestock species type to cover 60 percent of monthly feed/forage costs. The impact of more severe and longer-lasting future droughts on commodity markets could potentially increase these payments rates if feed/forage prices increase above and beyond economy-wide inflation. While modeling these future changes in LFP payment rates is outside of the scope of this assessment, this is an important avenue for future research to more wholistically capture increases in the financial climate risk of the LFP. Second, this analysis of the projected financial climate risk of the LFP assumes that the geography of livestock production and production practices will not adapt to changing climatic conditions. Climate change and the associated increasing intensity and duration of drought conditions may increase the risk and/or decrease the profitability of livestock production in some regions of the U.S. In response, some livestock producers may exit the market, relocate to other regions with more favorable production conditions, or adapt their production practices (e.g., reduce stocking rates) (Cheng et al., 2022). These adaptations would diminish the financial climate risk of the LFP provided adaptations make producers more resilient to drought conditions. Together, these assumptions, which potentially bias predictions of future program payments in differing directions, underscore the uncertainty inherent in the projections presented in this assessment. As such, these projections of future LFP payments do not constitute an upper or lower bound on future LFP payments and instead reflect plausible financial climate risks of the program with a high degree of uncertainty.

Emissions Scenarios

To project future drought conditions in the U.S. and associated LFP expenditures, this assessment considers 4 different emissions scenarios. These scenarios are referred to as Shared Socio-economic Pathways (SSP) defined by the Intergovernmental Panel on Climate Change (IPCC) and were designed to span a range of modelled greenhouse gas (GHG) emissions scenarios consistent with low to high warming levels. Specifically, this report considers the following SSP scenarios: SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5. These scenarios use the naming convention SSPx-y, where 'SSPx' refers to the SSP describing the socio-economic trends underlying the scenario and 'y' refers to the approximate level of radiative forcing (in Watts per square meter) resulting from the scenario in the year 2100.

Radiative forcing measures how much energy is coming into the atmosphere from the sun, compared to how much is leaving the atmosphere as infrared radiation. Prior to the industrial era, radiative forcing was balanced over extremely long periods of time, and Earth's temperature remained relatively stable. The addition of GHGs to the atmosphere through anthropogenic factors, as well as other changes in land use and natural systems effects, have altered this balance at an unprecedented rate, and now more heat enters the atmosphere than exits it. Below are additional details describing each of the SSPs modeled in the report.

Moderating Emissions (SSP1-2.6): Low GHG emissions, warming is limited to less than 2° Celsius by 2100. CO_2 emissions decline to net zero by 2070.

Middle of the Road (SSP2-4.5): Intermediate GHG emissions, warming is limited to less than 3° Celsius by 2100. CO_2 emissions remain around current levels until 2050.

High Emissions (SSP3-7.0): High GHG emissions, warming is limited to less than 4° Celsius by 2100. CO_2 emissions approximately double from current levels by 2100.

Accelerating Emissions (SSP5-8.5): Very high GHG emissions, warming exceeds 4° Celsius by 2100. CO_2 emissions approximately double from current levels by 2050.

The Financial Climate Risk of the Livestock Forage Disaster Program

Figure 3 presents results of future aggregate annual LFP payments and 95 percent confidence intervals through 2100 across a range of emissions scenarios and methods for classifying drought. Specifically, the top panel of Figure 3 shows projected LFP expenditures under the current USDM method where future drought classifications rely upon longer-term (60+ year) climate data to assess drought (stationarity drought classification). The bottom panel of Figure 3 plots projected LFP expenditures for the case where drought classifications are instead made based on decadally updated 30-year climate "normals" (non- stationarity drought classification). Average annual LFP expenditures for each of the four climate scenarios considered are plotted as lines with shaded areas around the lines representing the 95 percent confidence interval around the annual average. Projections of future LFP expenditures do not incorporate variance in climate model outcomes, which would significantly broaden the 95 percent confidence intervals around estimated means, particularly for projected expenditures in the latter years of the 21st century when climate model uncertainty is largest. Future aggregate LFP payments are presented as values in 2022 dollars to avoid additional assumptions regarding average inflation rates through 2100. Additionally, projected LFP payments do not incorporate potential future LFP payments made covering forage losses arising from wildfire on Federally managed grazing land.

Results demonstrate that if drought classification methods continue to rely on longer-term climate data (stationarity classification), then average aggregate LFP payments are likely to increase by the end of the century, particularly under higher greenhouse gas (GHG) emissions scenarios. In the high (SSP3-7.0) and accelerating (SSP5-8.5) emission scenarios, average annual LFP payments during the 2070 to 2100 time period increase by 113.7 percent (95 percent confidence interval (CI) [97.3 percent, 130.2 percent]) and 137.3 percent (95 percent CI [120.3 percent, 154.4 percent]), respectively, compared to average annual payments between 2014 and 2022.[7] These percent changes in LFP payments under the high and accelerating emissions scenarios translate to approximately \$0.8 and \$0.95 billion (2022 dollars) increases, respectively, in average annual payments from the 2014 to 2022 average by the 2070 to 2100 time period.

Payments do not increase as substantially in the lower emissions scenarios compared to higher emissions scenarios, as diminished rates of climate change decrease the severity and frequency of drought. Specifically, in the moderating (SSP1-2.6) and middle of the road (SSP2-4.5) emissions scenarios, average annual LFP payments during the 2070 to 2100 time period increase by 44.6 percent (95 percent CI [29.4 percent, 60.0 percent]) and 65.3 percent (95 percent CI [49.4 percent, 81.3 percent]), respectively, compared to average annual payments between 2014 and 2022. In dollar values, the moderating and middle of the road scenarios are associated with respective increases of approximately \$0.3 billion (2022 dollars) and \$0.45 billion (2022 dollars) in annual average program payments, compared to the 2014 to 2022 average, by the 2070 to 2100 time period.

Altering the current USDM methods used to detect and classify drought to rely on 30-year climate norms, updated decadally, attenuates projections of future LFP payments. In this scenario, increases in average aggregate annual LFP payments persist for higher emission scenarios while lower emission scenarios are associated with relatively small increases in average LFP payments by the end of the century. When drought is classified via non- stationarity methods, model results suggest that for the high (SSP3-7.0) and accelerating (SSP5-8.5) emissions scenarios, average annual LFP payments during the 2070 to 2100 time period increase by 26.6 percent (95 percent CI [12.3 percent, 40.9 percent]) and 42.3 percent (95 percent CI [27.2 percent, 57.4 percent]), respectively, compared to average annual payments between 2014 and 2022. These percent changes in LFP payments under the high and accelerating emissions scenarios translate to approximately \$0.2 and \$0.3 billion (in 2022 dollars) increases, respectively, in average annual payments from the 2014 to 2022 average by the 2070 to 2100 time period. Meanwhile, in the

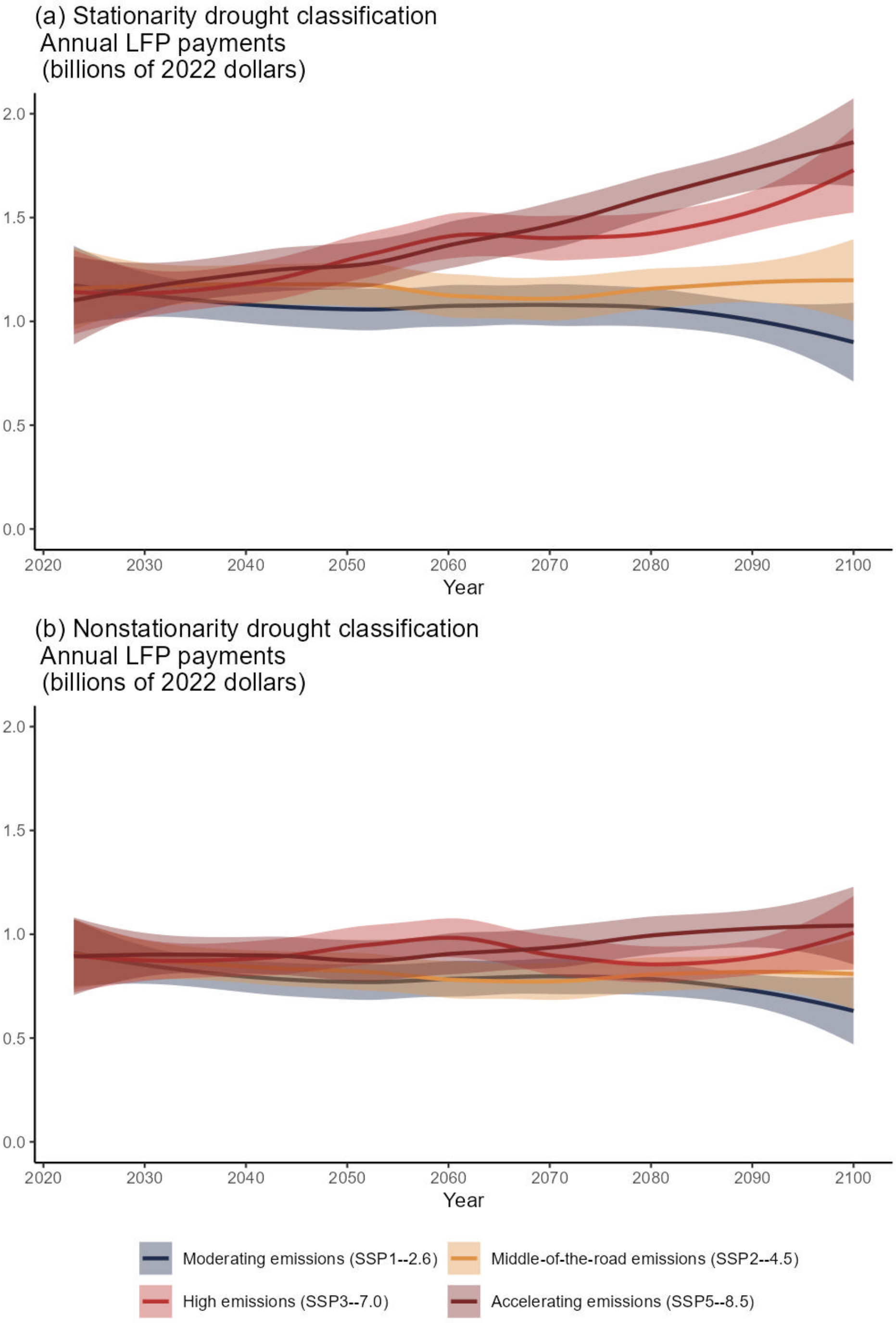
[7] Confidence intervals (CI) are ranges around an estimate that conveys the precision of the estimate. The 95 percent confidence interval refers to the range over which there is a 95 percent probability that the true value of the estimated statistic falls within.

scenarios of moderating (SSP1-2.6) and middle of the road (SSP2-4.5) emissions, average annual LFP payments during the 2070 to 2100 time period increase by 5.0 percent (95 percent CI [-8.1 percent, 18.0 percent]) and 13.8 percent (95 percent CI [0.2 percent, 27.5 percent]), respectively, compared to average annual payments between 2014 and 2022. In dollar values, the moderating and middle of the road scenarios are associated with respective increases of approximately $0.04 billion (2022 dollars) and $0.1 billion (2022 dollars) in annual average program payments, compared to the 2014 to 2022 average, by the 2070 to 2100 time period.

Comparing projections of future LFP payments generated under stationarity and non-stationarity drought classification methods highlights the importance of drought classification methods in characterizing the financial climate risk of the LFP. Specifically, if the methods used to detect and classify drought do not adjust to future changes in climatic conditions (e.g., aridification), then the LFP constitutes a potentially larger financial climate risk to the Federal Government's budget, particularly in higher emissions scenarios where average annual LFP payments increase in the 2070 to 2100 time period by more than $0.8 billion (2022 dollars) from their 2014 to 2022 average. However, if the methods used to detect and classify drought adapt to evolving climate patterns, then the LFP presents a potentially smaller financial climate risk, particularly in lower emissions scenarios where model results suggest that average annual payments may only modestly increase (2022 dollars) from their 2014 to 2022 averages by the end of the century. The projected increases in LFP payments under differing emissions scenarios are relatively small compared to current Federal government expenditures on the Federal Crop Insurance Program (FCIP). For example, average government expenditures supporting the FCIP averaged $8 billion per year between 2011 and 2021 (GAO, 2023). The projected increase in annual LFP payments of nearly $1 billion per year (in 2022 dollars) by the 2070 to 2100 time period under the high emissions, stationarity drought classification scenario constitutes approximately 12.5 percent of the current average annual Federal government expenditures allocated to supporting FCIP[8].

[8] See OMB (2022) "Climate Risk Exposure: An Assessment of the Federal Government's Financial Risks to Climate Change" for prior analysis conducted on climate related financial risk to the Federal Crop Insurance Program.

FIGURE 3: PROJECTED LFP PAYMENTS, 2023-2100



Note: This figure plots projected annual LFP payments and 95 percent confidence intervals around those projections between 2023 and 2100 for four differing emissions scenarios (see "Emissions Scenarios" text box for more information). The figure's top panel projects LFP payments using the current 'stationarity' methods for drought classification i.e., definitions for drought in a given region are based on 60 or more years of historical climate data. The figure's bottom panel uses a 'non- stationarity' method to classify drought i.e., definitions for drought in a given region are based on 30 years of climatic data and updated through time to reflect a changing climate (e.g., aridification or humidification). Projected future LFP payments are generated using parameter estimates from a panel data econometric model estimating the relationship between county-level aggregate annual LFP payments and the number of months of LFP payments producers within a county were eligible to receive (see Appendix B for more information). These parameter estimates are then combined with projected future drought conditions in the U.S. which distill future climate conditions into U.S. Drought Monitor classifications and months of LFP eligibility using 8 different climate change models (see Appendix B for more information on drought projections). For each climate change model, annual aggregate LFP payments are generated by multiplying econometric model parameters by the number of LFP eligible months projected by the model for each county and summing across counties. Annual results from each climate model are then aggregated and confidence intervals estimated using locally weighted (LOESS, locally weighted scatterplot smoothing) regression techniques (Cleveland & Devlin, 1988). Future LFP payments are expressed in real terms i.e., in 2022 dollar values.

Source: USDA, Economic Research Service using data provided by USDA, Farm Service Agency, parameter estimates generated by econometric modeling and projections of future drought conditions across differing emissions scenarios and models.

Conclusion

The USDA's Livestock Forage Disaster Program (LFP) provides payments to livestock producers whose forage production is impacted by drought. This assessment addresses the financial climate risk of the program using projected future LFP payments for a range of emissions scenarios and an ensemble of climate models. Projections of future drought conditions under climate change indicate that in many regions of the U.S., droughts will become more frequent and severe (Lehner et al., 2017; Leng & Hall, 2019; Zhao & Dai, 2017). This increase in the severity and frequency of drought poses a potential financial climate risk for the Federal Government's budget as it relates to LFP payments. Modeling results suggest that these drought risks may be significant, particularly in scenarios where emissions remain high and drought classification continues to be based upon deviations from longer-term climate (stationarity drought classification). In these higher emissions scenarios, model results indicate that future annual average aggregate LFP payments could increase by more than 100 percent (in 2022 dollars) by the end of the century compared to average payments between 2014 and 2022. Model results also highlight the importance of methods used for classifying drought under climate change (Parker et al., 2023). If the metrics used to classify drought are updated to reflect changing climate patterns (e.g., aridification), then the financial climate risk of the LFP diminishes as fewer producers become eligible for program payments. This analysis presents alternative drought classifications to represent their potential impact on LFP payments; however, neither this assessment nor its results take a position on broader considerations and consequences of modifying classification of drought.

This analysis of the financial-climate risk of the LFP makes two key assumptions that introduce uncertainty in projections of future LFP payments. First, the financial climate risk model assumes that livestock producers do not adapt to evolving climatic conditions. However, livestock producers may adapt to changing climate conditions by altering their herd sizes, production practices, and/or where they choose to operate which may diminish the climate financial risk posed by the LFP. Second, the analysis does not incorporate potential changes in LFP payment rates, which may increase if severe and consistent drought conditions impact commodity, feed, or forage markets. These potential LFP payment rate increases could increase the climate financial risk of LFP, as higher LFP payments would increase Federal Government LFP expenditures.

U.S. Department of Agriculture Forest Service and U.S. Department of the Interior: Update on Projected Wildland Fire Suppression Costs Due to Climate Change Impacts

Introduction

There is little doubt that changes in climate will affect wildlands, wildland fire, and suppression of fire (Abatzoglou and Kolden, 2013; Abt et al., 2009; Flannigan et al., 2005; Flannigan et al., 2006; Flannigan et al., 2016; Littell et al., 2009; Littell et al., 2016; Liu et al., 2014; McKenzie et al., 2016; Mitchell et al.; 2014, Prestemon et al., 2009; Riley et al., 2013; Riley et al., 2019; Westerling et al., 2006). Direct increases in area burned and numbers of large fires, resulting from more days with extreme fire weather, longer periods of sequential days with extreme fire weather, and longer fire seasons in many parts of the world are to be expected (Abatzoglou et al., 2021; Gao et al., 2021; Jolly et al., 2015; Lenihan et al., 2003; Riley & Loehman, 2016). Natural ignition patterns may change with shifting storm tracks and lightning occurrence (Romps et al., 2014), and there are likely to be changes in human ignition patterns due to land use change (Balch et al., 2017). Using an approach similar to that used in Hope et al. (2016), this analysis evaluates an aggregate set of data on U.S. Federal wildfire area burned and Federal suppression expenditures and projects both area burned and expenditures to calculate the effect of climate on Federal area burned and Federal expenditures in mid-century (2041-2059) and late-century (2081-2099). The USDA Forest Service (FS) evaluated area burned and wildfire suppression expenditures for both the FS and the U.S. Department of the Interior (DOI). The FS and DOI were modeled separately because their management objectives differ, as did data availability.

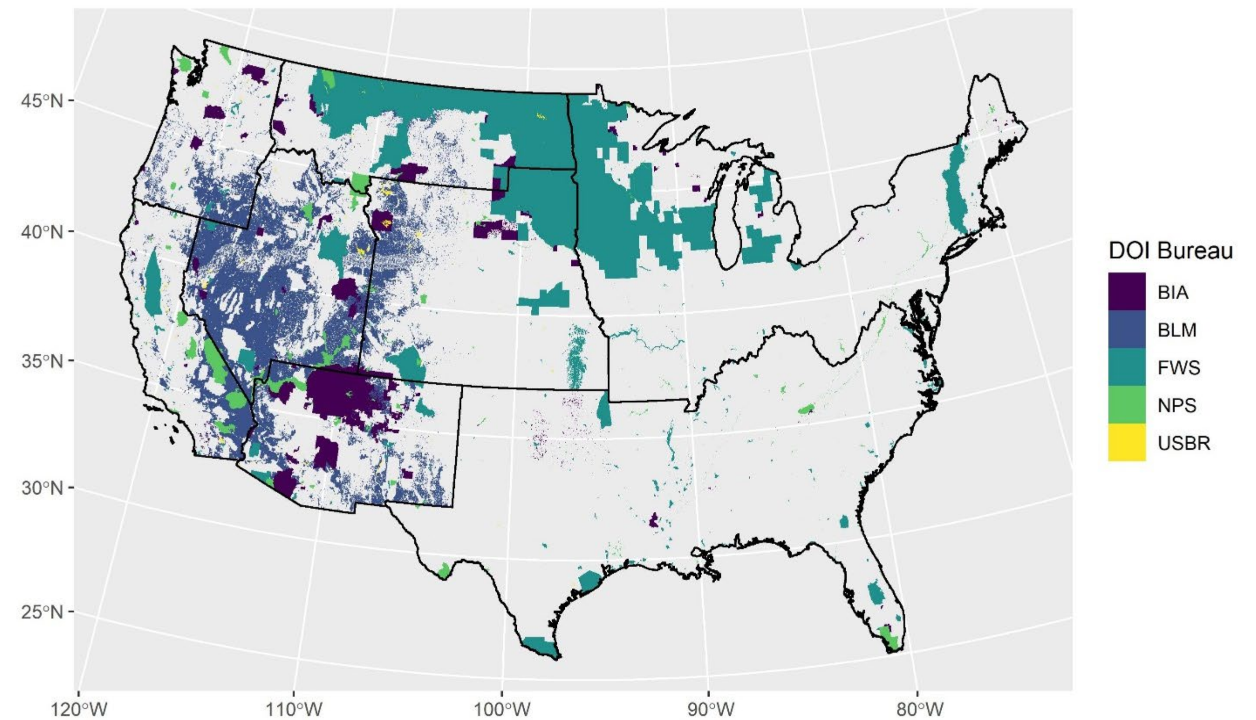
Background

Climate change is anticipated to raise land and sea temperatures globally, including in the U.S., and this change is likely to lead to shifts in the rate, severity, and extent of wildfire on Federal lands. Relevant to Federal budgets, such changes bring with them the expectation that spending to suppress wildfires and manage wildfire hazards would generally change as the climate changes. It is important to note that total costs and losses from wildfires are much larger than Federal government expenditures on preparedness and fire suppression. The economic burden of wildfires on the United States economy includes wildfire-induced damages and losses as well as the management costs to suppress and mitigate ignitions and fire spread.

The results given here (and detailed in Appendix C) extend similar work done in 2016 and 2021-2022. Similar to the previous reports published in the Budget, FS evaluates how changes in climate in the U.S. could lead to changes in annual spending to suppress wildfires on FS and DOI managed lands by the middle and the end of the current century. FS builds on the previous analyses by refining its models to improve fit, updating data on wildfire suppression expenditures through 2019 (from 2005 for the FS and 2013 for DOI), increasing the observation spatial resolution for suppression and wildfire, increasing the time span of historical wildfire to fiscal years 1993 through 2019, and expanding its consideration of the potential drivers of wildfires. Similar to the Analytical Perspectives chapter from fiscal year 2023, FS developed statistical models of wildfire based on historical data on climate and wildfire.

In the current effort, FS assembled an expanded set of projections by five global climate models (GCMs) and two alternative futures of radiative forcing levels (representative concentration pathways [RCPs] 4.5 and 8.5 Watts/m^2) through to the year 2099. Hence, FS shows projections of wildfire for five GCMs x two RCPs, i.e., 10 projections of future climate for the continental U.S. (CONUS). Observations on climate variables used in this analysis, vapor pressure deficit and the monthly average maximum daily temperature, were available from the MACAv2-METDATA for the conterminous U.S. at the 1/24th-degree grid scale assembled for the 2020 FS Resources Planning Act Assessment (USDA FS, 2023), which defined ten scenarios consisting of backcast historical (1993-2019) and projected future climate (2020-2099) from five GCMs under two RCPs (4.5 and 8.5 W/m^2). Observed historical data through 2015 were also available from MACAv2-METDATA while the observed historical data for 2015-2019 were from GRIDMET. Compared to the previous efforts, this effort refined the FS spatial resolution for wildfire projections to the National Forest level (from the Region level) and refined the DOI spatial resolution to the region by bureau level (from the region level Department-wide) (Figure 4, black lines) for each of eight CONUS regions defined by FS Region boundaries (Figure 5). Additionally, for the FS only, area burned models and the square root of area burned models used in the suppression spending modeling also included temporal lags of the area burned, extending back five years. Uncertainty analysis of the area burned models showed that, nationwide, the combination of average daily vapor pressure deficit (VPD) and average daily maximum temperature performed best when measured by bias and goodness of fit in out-of-sample prediction conditions across nearly all CONUS regions. FS suppression monthly expenditures by region were modeled for each region as a linear function of the sum across all wildfires of the square roots of current area burned in the region and its one-month lag. The Remainder of the FS (RFS) expenses, whose spending is not directly associated with particular regions, were modeled as the CONUS current-month total square root of area burned and its one-month lag. Suppression spending in Region 10 (Alaska) of the FS, comprising less than 0.06% of historical total agency suppression spending (2005-2019), was found to not be related to area burned in that region and therefore was assumed to have no significant financial effect on overall agency spending in the current analysis. Given warming trends and potential expansion of the Wildland-Urban Interface in Alaska, it might be useful to reevaluate this assumption in future analyses. Projections of spending for DOI were done by its four bureaus with significant wildfire: Bureau of Indian Affairs (BIA), Bureau of Land Management (BLM), U.S. Fish and Wildlife Service (FWS), and National Park Service (NPS). Expenditures for each of the DOI bureaus were modeled as a function of the bureau's current month CONUS total of the square roots of area burned and its one-month lag. Expenditures attributed to the Office of Wildland Fire (OWF) and Alaska were modeled as a function of the month's four-bureau CONUS total of the sum of the square root of area burned and its one-month lag. All spending projections were done with constant 2022 dollars. Uncertainty in the area burned and suppression spending for each climate projection was quantified using Monte Carlo simulations, where the regression models used to project area burned and suppression costs are fit using a random sample of data for each simulation. Overall uncertainty about climate was captured by projecting wildfire and spending under the ten projections (5 GCMs x 2 RCP scenarios, all assumed equally likely). The ten projections differed widely in their projected futures (by intention), with GCMs selected to capture a range of plausible futures in two climate dimensions: temperature and precipitation (Langner et al., 2020).

FIGURE 4. MAP OF DEPARTMENT OF THE INTERIOR LANDS BY BUREAU



Map of DOI lands delineated by the Protected Areas Database of the United States (PAD-US) version 3.0 by bureau used to generate the modeled historical and projected climate data used in the analysis for the department's lands, with regional boundaries defined by the eight CONUS Forest Service region definitions used in this analysis. FS Regions are demarcated in black lines. The PAD-US database version 3.0 defined the U.S. Fish and Wildlife Service administrative boundaries resolved only to the county level in parts of the upper Midwest and the northern Great Plains, where the Service's national realty boundaries depict numerous and small units spread across large geographic areas. [9]

This analysis identifies a single baseline for historical burned areas and suppression spending with which to compare future projections. The baseline is provided by modeled (backcast) historical area burned and spending, where climate variables were backcast by the GCM for fiscal years 1999-2019 and then areas burned and the sums of the square root of area burned used in the suppression spending models were projected to fiscal year 2099 from that climate backcast. For suppression expenditures, models were estimated based on data for 2013-2019 and projected

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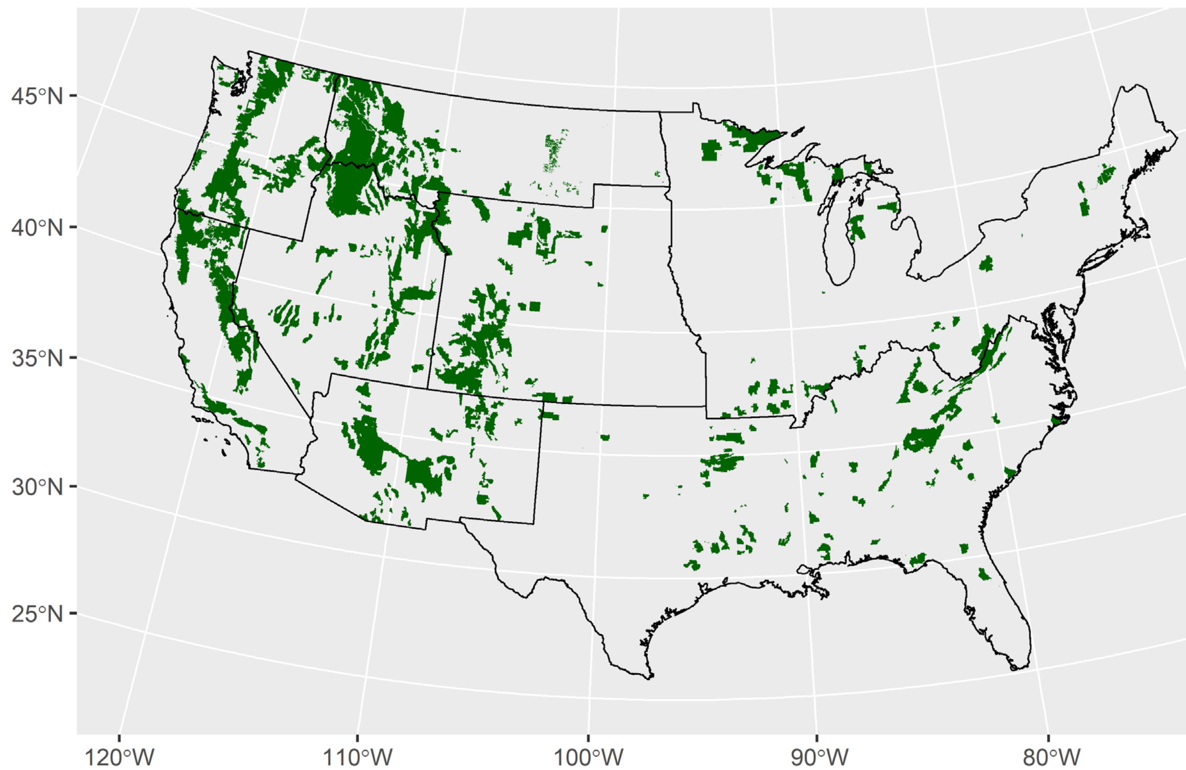
[9] See https://gis-fws.opendata.arcgis.com/datasets/745ed874c1394da3a9aae50267c9e049_0/explore?location=41.394176%2C-97.835079%2C5.92

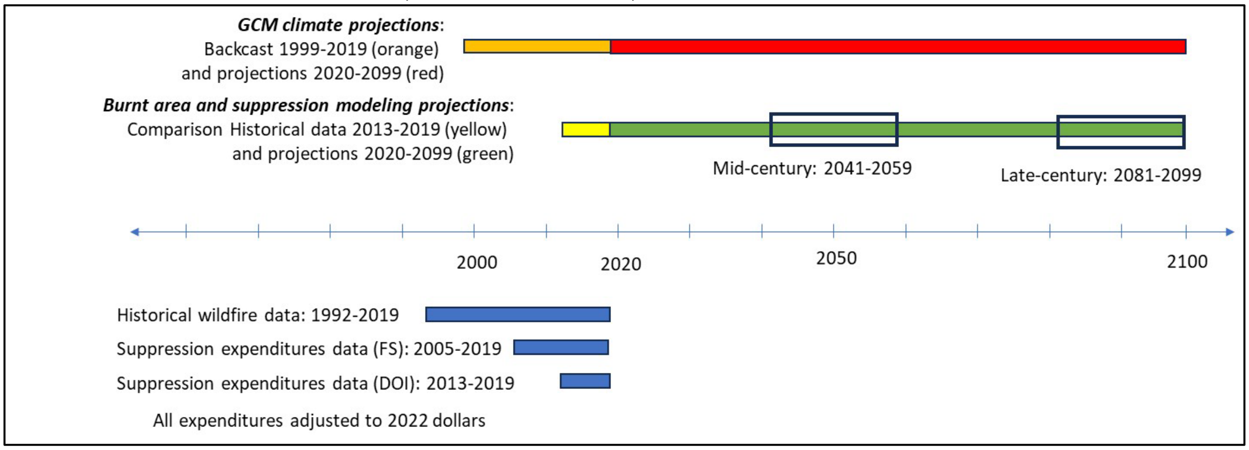
annually to fiscal year 2099. Projections were compared to backcast 2013-2019 area burned and suppression expenditures (Figure 6 describes the historical, comparison, and projected data time spans for this study). Using backcast data allows for consistent projections of magnitude changes in wildfire and suppression spending, reducing the effects of the biases contained in the underlying global climate models with respect to wildfire and spending. Percentage changes in area burned and spending using the backcast are then applied to observed historical information to adjust the modeled projections for the observed wildfire and spending starting points.

FIGURE 5. MAP OF FOREST SERVICE LANDS



Map of FS lands used to generate the modeled historical and projected climate data used in the analysis for the department's lands, with regional boundaries defined by the eight CONUS FS Region definitions used in this analysis in black.

FIGURE 6: HISTORICAL, COMPARISON, AND PROJECTED DATA TIME SPANS



Because the exponential function used in predicting wildfire would not be expected to generate a Normal probability distribution of projected outcomes, and because bootstrap samples were based on a limited span of historical time series data, FS considered median and percentile uncertainty levels as better representations of the probability distribution than the means, then calculated confidence intervals based on assumed Normality of predicted area burned and suppression expenditures. Results show that the median area burned, across both FS and DOI lands and across all climate projections, is projected to be 86 percent higher by mid-century (average from 2041-2059 projections) and 205 percent higher by late-century (average from 2081-2099 projections). (FS reiterates that these projected changes do not include any changes in area burned in Alaska.) Applying these percentage changes to historical area burned (excluding Alaska) for both FS and DOI, area burned is projected to rise from the 2013-2019 average of 3.77 million acres per year to 7.02 million acres by mid-century and 11.49 million acres by late-century. In this report, different from efforts in 2016 and 2021-2022, FS modeled suppression expenditures differently, as a function of the sums of the square root of area burned, resulting in an improved fit with spending. Nonetheless, because area burned and the sum of the square root of area burned are positively correlated, annual spending of both the FS and DOI are projected to rise. Compared to back-cast spending, fiscal years 2013-2019, in real, inflation-adjusted 2022 dollars, expenditures per year would rise by 40 percent by mid-century and 76 percent by late-century. Applying these percentage increases to observed historical spending, FS projects that total Federal spending for the FS and DOI would rise from a historical average (fiscal years 2013-2019) of \$3.35 billion per year to a projected \$4.69 billion per year in mid-century and \$5.90 billion per year by late-century. Additional detail of the area burned and spending projections are presented in Table 2 and an overview of area burned and suppression expenditure projections methods and results across FS and DOI lands combined are provided in Figure 7.

The statistical modeling approach used in this study and the projected results are conditional upon several assumptions, violation of any of which would alter both the projected changes in spending and the ranges of the uncertainty bands. Primary assumptions include that the biases and inconsistencies generated through aggregation of wildfire across space, omitted variables in model specifications, and model functional forms are small relative to projected changes in both wildfire and suppression spending. In addition, model parameter identification using historical wildfire and suppression spending includes the assumption that parameters do not change even while global climate models and likely spending patterns project an unprecedented climate future. It bears emphasizing, as well, that this analysis only considers *suppression* expenditures by FS and DOI, and excludes additional wildfire-related damages in terms of losses to property, natural resources, human health, or other economic costs, nor suppression expenditures by other private and public entities. As such, the analysis covers only part of the economic impacts of wildfires occurring on federally managed lands in the U.S. Additionally, because hazardous fuels were not directly modeled, no scenarios were analyzed to examine how Federal efforts to accelerate rates of hazardous fuel reduction would affect wildfire and suppression spending. Even with these caveats and assumptions, these models, along with the broader literature, provide evidence that both wildfire areal extent and suppression expenditures are expected to increase with climate change. The models show that temperature and vapor pressure deficit (and previous years' wildfire area burned, for the Forest Service models) effectively account for changes in monthly area burned and associated suppression spending[10]. The modeling results show that increases in area burned could plausibly triple and inflation-adjusted suppression spending could nearly double in this century.

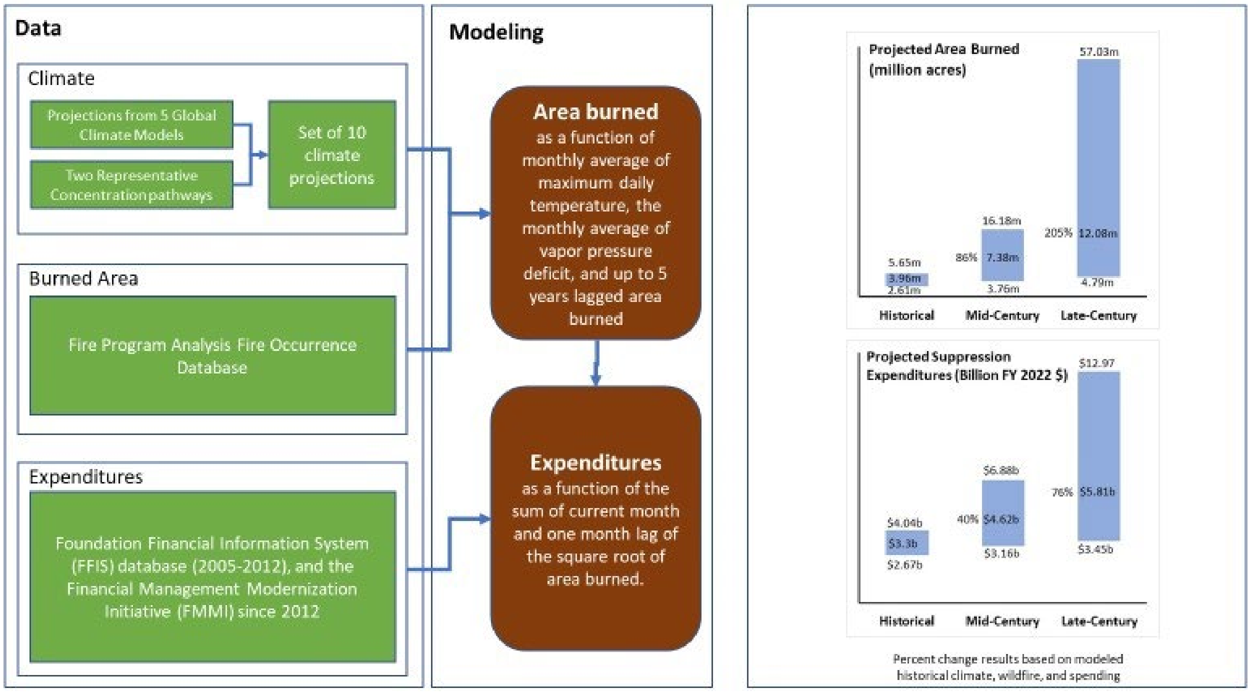
[10] Area burned models estimated over historical data had pseudo-R^2s ranging from 0.32 to 0.70 for the Forest Service and from 0.03 to 0.81 for Interior's four main bureaus; for spending, R^2s ranged from 0.14 to 0.78 for the Forest Service and 0.10 to 0.76 for the Department of the Interior.

TABLE 2: PROJECTED AREA BURNED AND SUPPRESSION EXPENDITURES FOR FOREST SERVICE
AND DEPARTMENT OF THE INTERIOR

Model	Time Period	Forest Service (FS)	Dept. of the Interior (DOI)	Combined FS + DOI
Area Burned	Mid-Century	98% [42%, 306%]	77% [43%, 163%]	86% [44%, 234%]
Area Burned	Late-Century	232% [29%, 2,488%]	171% [71%, 635%]	205% [73%, 1,399%]
Suppression Expenditures	Mid-Century	42% [20%, 84%]	31% [17%, 55%]	40% [19%, 81%]
Suppression Expenditures	Late-Century	81% [17%, 283%]	58% [26%, 173%]	76% [16%, 265%]

Detailed projections of area burned and suppression spending, by FS and DOI combined, percentage changes from modeled historical area burned (2013-2019) and spending (2013-2019) for mid-century (2041-2059) and late century (2081-2099) projections. Lower (5th) and upper (95th) percentile bounds for a 90 percent uncertainty band are shown in brackets. Large upper tails are connected to the exponential (Poisson Pseudo-Maximum Likelihood) functional form of area burned and to the wildfire outcomes generated from the climate predictions of the Hadley Centre Global Environment Model version 2 climate model (HadGEM2-ES365), which projects substantially hotter and drier conditions under both RCP 4.5 and 8.5 compared to the majority of the climate models included in this analysis. While the large tails are a function of the modeling used, it reinforces the practical consideration that there is considerable uncertainty inherent all of these projections. Despite that large uncertainty, even the lower bounds of all models indicate an increase in spending.

FIGURE 7: SUMMARY OF AREA BURNED AND SUPPRESSION EXPENDITURE PROJECTIONS METHODS AND RESULTS ACROSS FS AND DOI LANDS COMBINED



Note: 80% of area burned and suppression spending projected outcomes are contained within the values comprising the blue bars on the right side of this figure, i.e., an 80% model parameter and climate uncertainty bound.

Methods

Overview

This study extends similar work done in 2016 and 2021-2022 (Executive Office of the President, 2016; USDA FS, 2022). In the previous studies, FS used a two-step model approach where area burned was projected and subsequently used in a model of suppression expenditures. FS takes this two-step approach in this study also. However, FS refined the models in terms of: 1) spatial units of observation for both the FS and DOI area burned, 2) inclusion of previous area burned in the area burned (and square root of area burned) projection models, 3) the level of bureau aggregation for DOI spending, 4) the statistical relationship between suppression spending and area burned, and 5) a longer time series of observations for both wildfire and spending.

In the present study, the final burned area models for the FS were developed at the National Forest level and estimated as regional panel models with National Forests as the cross-sectional units, i.e., eight regional models, with individual National Forests given their own intercepts. For the DOI, area burned was disaggregated to the bureau level (i.e., BIA, BLM, FWS, and NPS; the Bureau of Reclamation was not included due to low wildfire propensity and limited spatial extent) and the physical region boundaries defined by FS Regions. In other words, the wildfire occurring in each CONUS region was allowed to differ in its relationship of area burned to climate variables. For DOI, area burned models were estimated separately for each of the bureau-region spatial units, a total of 30 models (no BLM area burned or square root of area burned models were estimated for Regions 8 and 9). The statistical relationships between area burned (and the sums of the square roots of area burned for each spatial and temporal unit, used in the suppression expenditure models) were specified as Poisson pseudo-maximum likelihood (PPML) models with variables of monthly maximum temperature and vapor pressure deficit (e.g., Motta 2019);[11] For FS models, the lags of annual sums of area burned for t-12, t-24, t-36, and t-48 months were additionally included, which were intended to capture the fuel-treatment effects of wildfire, which could potentially reduce area burned in the current month. This combination of variables for projected area burned performed better out of sample (random and end of series hold-out) than alternatives (linear, log-transformed area burned).[12]

Log-transformation of maximum temperature (in degrees Kelvin) and VPD in the PPML specifications slightly improved the out-of-sample goodness-of-fit (as measured by root mean squared error and bias) of the area burned projections compared to leaving temperature and VPD untransformed.

For model fitting on suppression expenditures, FS had consistent monthly data for each region of the FS from 2005-2020. For DOI, monthly suppression expenditures were available for each bureau, 2013-2020. However, due to some missing observations in area burned and square root of area burned for 2020, statistical model fitting stopped at 2019 for both the FS and DOI.

Variable Preselection and Model Formulation for Expenditures

FS initially tested regression models of suppression expenditures as a function of area burned to evaluate model feasibility, and FS found that these models performed well in out-of-sample conditions, particularly when compared with univariate time series models (i.e., modeling spending as a function of lags of spending and seasonal components). FS again opted to exploit the monthly frequency of expenditure data and specify expenditures separately for each of FS Regions 1-9 with two-stage least squares (2SLS) methods, with expenditures in the region as a function of instrumented current month sum total of the square roots of area burned for the wildfires in the region and the one-month lag of this variable (not instrumented) in the region. Instruments for the current month square root of area burned was the current number of fires reported in the National Forests in the region. For FS Region 10 (Alaska), expenditures were not

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[11] The assumption of a constant mean/variance proportion restriction of the PPML model could have been relaxed with estimation of other functional forms. See the Variable Preselection and Model for Area Burned section for additional explanation of the choice of the PPML model.

[12] In the current effort, in addition to climate, for national forests managed by the FS only, the inclusion of prior years' annual total areas burned was motivated by previous research that showed that prior years' area burned is negatively correlated with current area burned. That research showed that such effects can be identified for spatial aggregates about the same size as (or smaller than) a national forest (e.g., Prestemon et al., 2002). The mechanism captured by inclusion of lags is that wildfire consumes fuels, which reduces the probability of (area burned by) wildfire in the coming years. Out-of-sample tests showed that area burned and square root of area burned predicted by models that included climate and lagged wildfire performed as well as or better (lower error, less biased) than models that included only climate variables. For DOI lands, however, tests showed that models that included climate and lagged area burned performed worse than those that only included climate, implying that high levels of data aggregation prevented identification of this lagged wildfire effect on area burned and square root of area burned.

modeled , due to a lack of climate projections using the same set of GCM's and also because such expenditures comprised only 0.06% of historical wildfire suppression spending for the agency, 2005-2019. For the rest of the FS (covering national contracts, the Washington, DC, office, and research stations), expenditures were also modeled as a function of the current month square root of area burned on all national forests in regions 1-9, with current square root of area burned instrumented by the total number of wildfires on national forests in regions 1-9. Because DOI expenditures were not available for physical regions like the FS, bureau total and OWF expenditures, also reported monthly, were modeled with 2SLS methods, with expenditures specified as a function of current month square root of area burned (instrumented with the number of wildfires on DOI lands across all of CONUS and its one-month lag.). Models of area burned and square root of area burned for the DOI were built using acres and sums of square root of acres (and fire counts, needed for instrumenting the expenditure models), aggregated by bureau and by the same regional boundaries as the FS uses.

Because stationarity is required for regressors in the models described above, FS also carried out several tests (augmented Dickey-Fuller, DFGLS, Phillips-Perron) of stationarity of the time series of real dollar monthly expenditures at the regional level for the FS and the national level for DOI. All Phillips-Perron stationarity tests rejected a unit root at stronger than 1 percent for all FS Regions, RFS, and for the aggregate of DOI expenditures. Dickey-Fuller generalized least squares tests rejected stationarity for FS Regions 1, 2, 8, 9, 10, and RFS when specifying lagged difference terms using the Schwarz Information Criterion but less commonly under other optimization criteria. FS therefore evaluated the existence of long-term stable relationships (cointegrating relations) between RFS spending and CONUS area burned on FS lands, and between DOI spending and CONUS area burned on DOI lands with a Johansen cointegration rank test for these two series. Rank tests could not reject nulls of no cointegration. FS therefore retained models of expenditures in levels as a function of the sums of the square roots of area burned in levels for the projections reported here.

With monthly data on expenditures, it is natural to consider the existence of seasonal effects in spending that need to be accounted for. However, for the expenditures of the FS and DOI, in nearly every case in every region, seasonality—measured with month indicator (dummy) variables—was found to be not statistically significant, after controlling for the square root of area burned. Therefore, FS ignored potential seasonality in the expenditure models.

Finally, given the possibility of serial correlation in spending, FS tested for residual serial correlation in the second stage equations of FS's suppression expenditure models. Durbin-Watson tests on the residuals confirmed nonsignificant serial correlation.

Variable Preselection and Model Formulation for Area Burned

Given accepted research, it has been shown that area burned in the U.S. can be adequately and accurately modeled as a function of temperature, moisture, and a variety of indices that derive from those two variables that determine flammability and rate of spread of wildfire. In the 2022 report FS tested a suite of climate variables that have been projected into the future by the Global Climate Models, downscaled using the Multivariate Adaptive Constructed Analogs (MACA) process (Abatzoglou, 2013; Abatzoglou and Brown, 2012). These climate variables included monthly average of daily maximum temperature, monthly total of daily precipitation, monthly average of vapor pressure deficit (VPD) and monthly total potential evapotranspiration (PET). In the 2016 study, the single climate variable selected for inclusion in the 2016 model was the fiscal year annual average of daily maximum temperature while in the 2021 model FS chose to use monthly, regional observations of monthly average of daily maximum temperature and VPD. See the 2022 report for additional details on testing climate variables for inclusion. For this version of the model, based on past results, FS chose to only consider monthly average of daily maximum temperature and VPD. Temperature has been shown to influence fuel moistures, fire season length, extreme fire weather, and lightning and storm tracks—all conditions that are known to influence area burned (Flannigan et al., 2009; Flannigan et al., 2016; McKenzie et al., 2004; Mueller et al., 2020; Romps et al., 2014; Wang et al., 2015). Abatzoglou and Kolden (2013) state that area burned is influenced by temperature, precipitation, and drought but contend that using temperature is merely a proxy for the many ways climate can influence wildfire. Vapor pressure deficit (VPD) is a metric incorporating both temperature and relative humidity. VPD indicates how much moisture is in the air relative to the maximum amount of moisture that the air could hold. VPD has also been shown to correlate strongly with large fire events and area burned (Mueller et al., 2020; Seager et al., 2015; Williams et al., 2019).

Research on human-caused fires indicates that local population and income can influence ignitions (Mercer and Prestemon, 2005; Prestemon et al., 2013; Balch et al., 2017) and area burned (Prestemon et al., 2016). In addition, anecdotal evidence implies that as population increases, buildings and other structures increase, which diverts suppression efforts from land protection to point protection. This, too, could lead to increases in area burned, all else held constant. Increases in income are hypothesized to influence the extent of local power and influence, which has been shown to lead to increased suppression expenditures (Donovan et al., 2011). Such effects have been identified at small spatial scales, at the level of the county or smaller. However, less research exists on such relationships at such large spatial scales as whole collections of national forests (e.g., FS Regions). In the 2021-2022 effort, FS found that tests of area burned models for FS Regions that included population in the counties containing national forests or DOI lands revealed no significant population effects. Therefore, in the 2023 effort, FS did not consider population in models of either National Forest-level wildfire or DOI bureau-region wildfire.

Modeling of area burned should address the zero bound on area burned. One way to recognize this is through either log-transformation of area burned (assuming no months with zero area burned, in this case) or the application of models such as the Tobit or pseudo-Poisson maximum likelihood specifications. In the 2021-2022 effort, FS evaluated linear models (which ignored zero-truncation) and PPML and negative binomial pseudo-maximum likelihood (NBML) models in out-of-sample forecasting conditions over historical data. FS found that PPML models out-performed linear models (and the NBML models, which additionally sometimes failed to converge in estimation) and avoided the possibility that projected area burned would be negative. For the 2023 effort, FS similarly evaluated PPML versus NBML models for wildfire area burned and square root of area burned and found that that the PPML models had no issues in maximum likelihood convergence and yielded low-bias out-of-sample predictions in the historical data.

Therefore, FS opted to model area burned using PPML models, as a function of monthly maximum daily temperature in degrees Kelvin, transformed by the natural logarithm, and monthly average vapor pressure deficit, also log-transformed. Exceptions to the two variable specifications were made for BLM lands in regions 2, 4, 5, and 6, for which maximum temperature was dropped. Finally, and for the national forests only, FS additionally included 12-, 24-, 36-, and 48-month lags of running totals of the prior twelve months' area burned.

The models FS selected projected area burned as a function of the monthly average of maximum daily temperature and the monthly average of vapor pressure deficit (VPD) (and lagged areas burned in the Forest Service models for national forests). This combination of variables for projected area burned, although very highly correlated in the historical time series ($r > 0.92$ in all regions evaluated), performed better out of sample (random and end of series hold-out). Log-transformation of maximum temperature (in degrees Kelvin) and VPD (in kPa) slightly improved the out-of-sample fitness of the area burned projections.

Modeling area burned requires some strong assumptions, that, in the face of a changing climate, could be difficult to justify. FS expects climate change to alter forest and range ecosystem compositions, and vegetation changes will, in turn, alter how many acres burn and how often and intensely they burn. To account for vegetation changes related to hazardous fuels, FS tested models that included variables related to fuels in the FS models. FS used information available in the FS's Forest Inventory and Analysis (FIA) database on annual dry biomass per acre of fine and coarse woody debris, as well as total basal area per acre by national forest (Burrill et al., 2022). The FIA program conducts an inventory of the nation's forest land based on information collected from forest plots by field crews. The FIA information can be used to calculate statistical estimates of forest characteristics across geographic domains of interest, such as individual national forests. FS used FIA information because it is the best source of consistent information on forest conditions over time. Annual estimates of total basal area were available by national forest for 2005-2019. However, FIA field crews only began collecting data related to fuels, including information fine and coarse woody debris, starting in 2012, and only collect those data on a subset of field plots on many national forests. Therefore, estimates of fuels variables for all years in the study period were not available. To obtain annual estimates for the fuels variables by National Forest for each year in the study period, values for missing years were interpolated from available estimates. To facilitate modeling, these temporally interpolated fuels variables were further smoothed with a centered 25-month linear temporal smoothing algorithm and then lagged 13 months to avoid simultaneity biases in equation estimation.

Models of FS area burned that incorporated one or more of the fuels variables or basal area per acre did not perform as well as the models with climate and lagged wildfire. The poorer performance of those models is likely due at least in part to the sparsity of the fuels variables relative to the monthly climate and lagged wildfire variables in the models, which reduced the number of usable observations. Other efforts are beginning to model and map those variables consistently through space and time, and once those data sets are available for the years in the study period, they could be tested in area burned models in future studies. Alternatively, fuels information may only be of limited importance to determining area burned at aggregate levels such as national forests. While fuels are important for determining fire regimes, other studies have shown limited statistical relationships between fuels and area burned. In addition, previous work has found that suppression expenditures may increase or decrease with the addition of previous fires to the landscape, in part due to additional suppression opportunities that may not have been available without the previous fire (Belval et al., 2019).

Fuels and related variables were not tested in models of area burned for DOI lands because of the poor performance of the FS models and because fuels data on DOI lands was more sparsely collected than it was for national forests.

In this analysis, because hazardous fuels are not directly modeled, estimated models carry an assumption that these vegetation changes, after accounting for historical wildfire (for FS lands only), will not matter to either area burned, the square root of area burned, or (by extension) to the expenditures the FS and DOI make to suppress wildfire. It is possible that, to the extent these changes have already begun to occur across Federal wildlands, these models incorporate some of these changes in ecosystems, but FS cannot test this possibility using an aggregate model structure alone. Likewise, projections assume that parametric relationships only account for the effects of wildland hazardous fuels management efforts that have been taking place in the historical time period. Because FS does not include variables directly indexing such management, no what-if scenarios were carried out that would evaluate how Federal efforts to accelerate rates of hazardous fuel reduction would affect wildfire and suppression spending. Detailed vegetation modeling would be required to determine the extent to which climate-induced and management-caused changes in hazardous fuels would occur and therefore have effects on wildfire and suppression expenditures.

Data

Temporal and geographic extent: The expenditure data are monthly, based on the Federal fiscal year (October 1 to September 30). FS divided the U.S. into regions that coincide with the FS Regions and roughly with the Geographic Area Coordination Centers of the National Interagency Fire Center. Climate data are monthly also and are aggregated to these regions based on Federal lands only. Fire data, also monthly, are based on actual fire ignition locations from the FPA FOD (fiscal years 1992-2019) (Short, 2023). Monthly expenditure data for DOI are available separately for each of the main DOI bureaus (i.e., BIA, BLM, FWS, NPS) and for OWF, while consistent monthly data for the FS are available nationally for fiscal years 2005-2019 by FS Region. Given the varying starting and end-dates of wildfire and suppression data, model data used in this study were truncated at the end of fiscal year 2019.

Alaska (Region 10) was excluded from the analysis for several reasons. Spending in Alaska (Region 10) for the FS is low, averaging less than $1.5 m/year (0.06 percent of all FS spending, 2005-2019, in inflation-adjusted FY 2022 dollars). Area burned on FS lands in Alaska (Region 10) also comprised less than 0.06 percent of historical wildfire for the FS. Furthermore, FS lacked for this study monthly data on projected climate corresponding to the two national forests in the state, precluding projections of wildfire using climate data. Hence, in the current study, FS does not model or consider FS spending in Alaska. Compared to the national forests of Alaska, wildfire area burned on DOI lands in the state is more significant. Alaska represents a significant acreage in many years (averaging 33 percent, 1992-2019, but ranging from 3 percent to 93 percent of total DOI area burned), but a much smaller expenditure share: the average was 8 percent, and the range was 4 to 13 percent of total real dollar DOI expenditures, fiscal years 2013-2019. For DOI, expenditures on Alaska wildfires are relatively low on a per-acre basis, as well. For example, in 2019, 69 percent of all acres recorded on DOI lands nationwide were in Alaska, yet Alaska suppression expenditures were 10 percent of the departmental total. Like for the FS national forests, FS lacked a climate projection for the lands managed by the four main DOI bureaus in Alaska, preventing a wildfire projection for any of the bureaus in the state. However, when modeling expenditures for DOI bureaus, spending recorded for each of the bureaus included the spending incurred in Alaska. Because FS modeled expenditures at the DOI bureau level and for OWF, which included spending on suppression in Alaska, models of expenditures for each of the bureaus and the OWF do account for the average effect of Alaska wildfire on DOI spending. FS considered adding the square root of area burned historical average to the individual bureau expenditure models, but the effect of its addition was minimal, as it would have the statistical effect of changing mainly the intercept terms and would not alter the spending projection.

FS used the FS's 2020 Resources Planning Act Assessment (RPA) climate projections, which comprise 5 climate models projecting under the Representative Concentration Pathways (RCPs) RCP 4.5 and RCP 8.5 scenarios (Langner et al., 2020; USDA FS, 2023). The RPA climate data set is a subset of the MACAv2-METDATA set (Abatzoglou & Brown, 2012; Abatzoglou, 2013). Global climate historical modeled projections (1950-2005) and future projections (2006-2099) from the Coupled Model Inter-Comparison Project 5 (CMIP5) were downscaled to the 4-km grid size using the Multivariate Adaptive Constructed Analogs (MACA) method. The MACA method is a statistical downscaling method that uses historical observations to remove historical biases and match spatial patterns in climate model output.

The RPA data set contains the historical data (METDATA, 1979-2015), and the historical modeled data (1950-2005) and the future projections (2006-2099) (MACAv2-METDATA) for 5 climate models under two Representative Concentration Pathways (RCP 4.5, 8.5) (Appendix C, Table C.1). Five climate models were selected to capture the future mid-century (2041-2059) range of the 20-model MACAv2-METDATA set (Langner et al., 2020). Rather than use an ensemble, a model that projected future change near the mean of all 20 projections was selected: NorESM1-M. The five models reflect the hottest projection (HadGEM2-ES365), the least warm projection (MRI-CGCM3), the wettest projection (CNRM-CM5), the driest projection (IPSL-CM5A-MR), and the middle of the range projection (NorESM1-M) (see http://maca.northwestknowledge.net/GCMs.php for detailed descriptions of these models). The data set and metadata are available at:

- Historical: https://www.fs.usda.gov/rds/archive/catalog/RDS-2017-0070-2
- Projections: https://www.fs.usda.gov/rds/archive/catalog/RDS-2018-0014

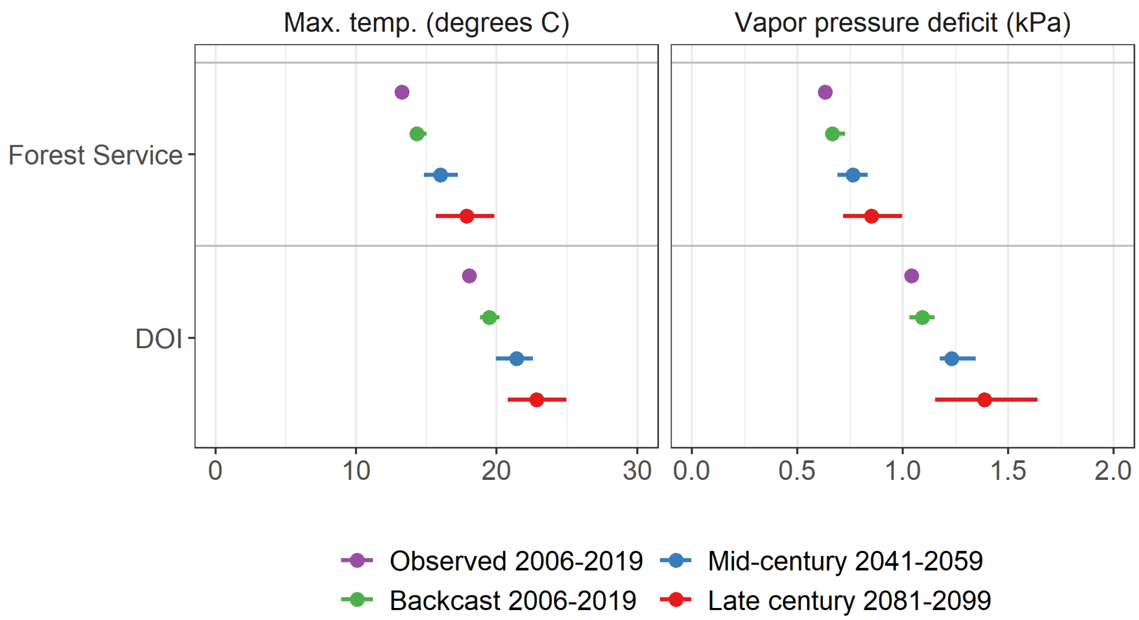
For this project, FS added monthly vapor pressure deficit from MACAv2-METDATA to the RPA historical and projected climate data sets. FS also added four years' worth of monthly data to all variables in the RPA historical data set (2016-2019) from GRIDMET, which is the data set from which the RPA historical data were derived (Abatzoglou, 2013).

FS generated regional and national averages, monthly and annual, for maximum daily temperature and average VPD. FS created regional monthly averages by first converting all daily or monthly spatial data to Albers Equal Area Conic to ensure grid cells from differing datasets matched and included only grid cells corresponding to Federal lands (FS or DOI) (Snyder, 1987).

Most of the global climate models available in the MACAv2 data set have been evaluated for their performance relative to historical climate observations. Based on the analysis by Sheffield et al. (2013), at the conterminous U.S. scale, the models that had the least bias in temperature included MRI-CGCM3, used in this study. For precipitation, the models with the least bias included CNRM-CM5 and NorESM1-M, used here. At the regional scale, the models that performed best included IPSL-CM5A-LR, used in this analysis. Simulations of the 20th century by CMIP5 models have been conducted for regions of the U.S.: Pacific Northwest (Rupp et al., 2013), Southeast (Rupp, 2016), and for the Southwest (Rupp Pers. Comm.). Based on these regional analyses, the top five models, based on 18 metrics, included CNRM-CM5 and HadGEM2-ES, used in this analysis.

Figure 8 shows the historical and projected maximum temperature and vapor pressure deficit area-weighted for nationwide by agency for the observed period and all modeled periods. The values of each variable during each time period differ by agency, but there are some trends to note. First, for both variables, values are higher for DOI lands than for FS lands in the observed and backcast data, and that remains the case in the future periods. Second, for each agency, the median values across the ten futures for both variables are greater in the two future periods than for the backcast and observed periods, indicating increasingly hotter temperature extremes, and drier conditions expected on average. Compared with backcast values, maximum monthly temperatures for both DOI and FS lands under RCP 8.5 are expected to increase by nearly 2 degrees Celsius by mid-century and more than 3 degrees Celsius by late century on average across the 10 futures, with the greatest increases projected under the hottest (HadGEM2-ES365) and driest (IPSL-CM5A-MR) projections for both agencies. Average projections of VPD for the U.S. across the ten futures show expected increases by 0.1 kPa at mid-century and 0.2 kPa at late century for FS lands, and by 0.2 and 0.3 for DOI lands for the two time periods, respectively. In all cases for both variables and both agencies, the range in average values across the ten futures for the U.S. is greater at late century than for mid-century, corresponding with increasing uncertainty in the climate model projections over time. While the projected values for both variables differ by region, there are consistent trends by region (Appendix Figures C.1 and C.2). Increases in both maximum temperature and VPD are also expected for each region at mid-century and late century. Average projected maximum temperature was greatest in the Southern region for both agencies at mid-century and late century, while the greatest increases in maximum temperature were projected in the Eastern region. For VPD, on average across the ten futures, the greatest values were projected for FS lands in the Southwestern region and for DOI lands in the Pacific Southwest, while the greatest increases were projected for both agencies' lands in the Southwestern region.

FIGURE 8: AVERAGE (MEDIAN) MONTHLY MAXIMUM TEMPERATURE AND VAPOR PRESSURE DEFICIT ON FOREST SERVICE AND DEPARTMENT OF THE INTERIOR LANDS FOR THE HISTORICAL OBSERVED PERIOD (2006-2019) AND FOR THE TEN PLAUSIBLE PROJECTED CLIMATE FUTURES (5 GCMS X 2 RCPS) USED IN THE PROJECTIONS FOR THE BACKCAST (2006-2019), MID-CENTURY (2041-2059) AND LATE CENTURY PERIODS (2081-2099).



In the backcast, mid-century, and late century periods, the point indicates the median of average values across all ten plausible futures, while the bars represent the range in average values across all futures.

Area burned (in acres) and number of fires were provided by Karen Short from the Fire Program Analysis Fire Occurrence Database (Short, 2023). This dataset includes point locations, discovery dates, and final area burned estimates from individual agency fire reports estimates that were aggregated by month and jurisdictional agency for fiscal years 1992 to 2020. FS was unable to acquire and properly compile complete fiscal year 2020 data from DOI due to time constraints.

Suppression expenditure data: All expenditures are in constant 2022 dollars (obtained from the President's Budget, "Table 10.1—Gross Domestic Product and Deflators Used in the Historical Tables: 1940-2026", at https://www.whitehouse.gov/omb/historical-tables/). Regional expenditure and RFS expenditure data for the FS were monthly, 2005-2020. For the DOI, data were also monthly, 2013-2020. The national-level data are from NIFC, and the FS regional data are derived from historical reports, the Foundation Financial Information System (FFIS) database (2005-2012), and the Financial Management Modernization Initiative (FMMI) since 2012.

Projections

To provide context for the wildfire and suppression projections, FS generated backcasts of area burned (1999-2019) for both the FS and DOI using backcast climate data and observed wildfire data. For suppression spending, FS generated backcasts also from 1999-2019 but, because monthly observations on spending by DOI were only available from 2013 onward, FS opted to compare all projections to mid- and late-century, in both area burned and suppression spending, to a common 2013-2019 historical time frame of reference. The projections for midcentury represent an average of 2041-2059, and late-century are an average of 2081-2099 (the year 2100 is not included in the MACA dataset).

FS used the projected climate data in the selected models to generate future area burned and the sums of square roots of area burned for all spatial and temporal units for midcentury and late-century, and then used the square root of area burned in the expenditure projections. In other words, the area burned projections are provided for context in the current effort and for comparisons with the 2016 and 2021-2022 efforts. FS also calculated a change in area burned from recent to the two future periods. There are two possible methods of projecting with the climate values from the GCMs: (1) use the historical observed data as the base and use the projected climate data to estimate the change, or (2) use the climate model backcast projection as the base and the projected data as the change. FS applied only the latter, as it likely reduces the effects of biases generated by the individual climate models, particularly when converted to percentage changes. The percentage changes, however, can be applied to the observed historical area burned and expenditures to offer a consistent picture of the effects of climate on both wildfire and suppression spending.

The Monte Carlo simulations involved (1) randomly sampling from monthly observations of area burned and backcast historical climate over fiscal years 1999-2019, monthly observations of FS suppression expenditures over fiscal years 2005-2019, and monthly observations of DOI suppression expenditures over fiscal years 2013-2019; (2) estimating statistical relationships for area burned and suppression spending with the randomly sampled data; (3) projecting area burned and spending through fiscal year 2099 with the estimated parameters; and (4) repeating steps (1)-(3) 50 times for each of the climate projections (each of the 10 GCM x RCP combinations). Monte Carlo projection results are summarized in terms of medians of area burned and expenditures, 80 percent and 90 percent upper and lower bounds of area burned and expenditures, and then medians across each of the 10 climate projections. FS generated projected expenditures and area burned for each of the climate models. Results were also summarized in tabular form, reporting historical observed, historical modeled (fiscal years 1999-2019) for area burned and expenditures for the FS and DOI and their total, including 80 percent and 90 percent upper and lower bounds and medians for mid-century and late-century.

Results

Area burned modeling results

Area burned model estimates are reported in Appendix C Tables C.1-C.3. Models indicate good fit and high significance of both maximum temperature and VPD. Constant terms are also significant in most cases. Pseudo-R^2's (not shown) indicate that a sizeable portion of historical variation is explained by the data in most regions for both agencies[10]. Generally, VPD is positively related to area burned. In cases when maximum temperature is included as an additional predictor, maximum temperature is negatively signed. Because maximum temperature is positively correlated with VPD, these results are not surprising. For any given value of VPD, a lower temperature means that relative humidity is lower, and thus fires would be expected to burn hotter.

Expenditure modeling results

Expenditure equation estimates are reported in Tables C.4-C.5. Models indicate that square root of area burned in the current month, instrumented with the number of reported wildfires, was only sometimes significant, while its one-month lag was typically significant and positive for each region (FS) and bureau-region (DOI) modeled.[13]

Projections

Area Burned Projections

Area burned projections for the FS and DOI in aggregate are shown in Figure 9, Figure 10, and Figure 11. (Regional detail of median area burned across all climate projections is presented in Appendix figures C.3-C.5.) The left panel of each of these figures reports the median and the upper and lower bounds of an 80% confidence band for the total of FS plus DOI (48-state CONUS). The confidence bands only account for parameter uncertainty in the area burned models across the ten climate projections. The right panel in each displays the median for each of the ten climate projections. Figure 9 is for total (FS + DOI), Figure 10 is FS only, and Figure 11 is DOI only. In all figures, it is apparent that late-century area burned varies widely across projections, with the highest area burned projected by the HadGEM2-ES365 (hot) climate model under the RCP 8.5 scenario. The lowest area burned projections emerged from the least-warm model, MRI-CGCM3 under the RCP 4.5 scenario. The figures demonstrate clearly how late-century area burned varies widely across climate projections, a result that might have been expected, given the wide variability across projections in late-century maximum temperature and VPD (Figure 8).

[13] The pattern of current-month statistical non-significance and lagged month statistical significance is attributable to how wildfires and spending are assigned to particular months and to the common delay in recorded spending. Wildfire area burned is recorded for the month in which the wildfire starts, but it can burn into the following month and generate costs in that following month that are assigned to that following month. Furthermore, even wildfires extinguished in the current month often have costs recorded the following month.

FIGURE 9: TOTAL DEPARTMENT OF THE INTERIOR + USDA FOREST SERVICE AREA BURNED, PROJECTED, BY FISCAL YEAR, ALL CLIMATE PROJECTIONS COMBINED, AND MEDIAN BY SCENARIO. MONTE CARLO 50 ITERATIONS PER GCM X RCP SCENARIO (I.E., 500 ITERATIONS INCLUDED IN THIS FIGURE).

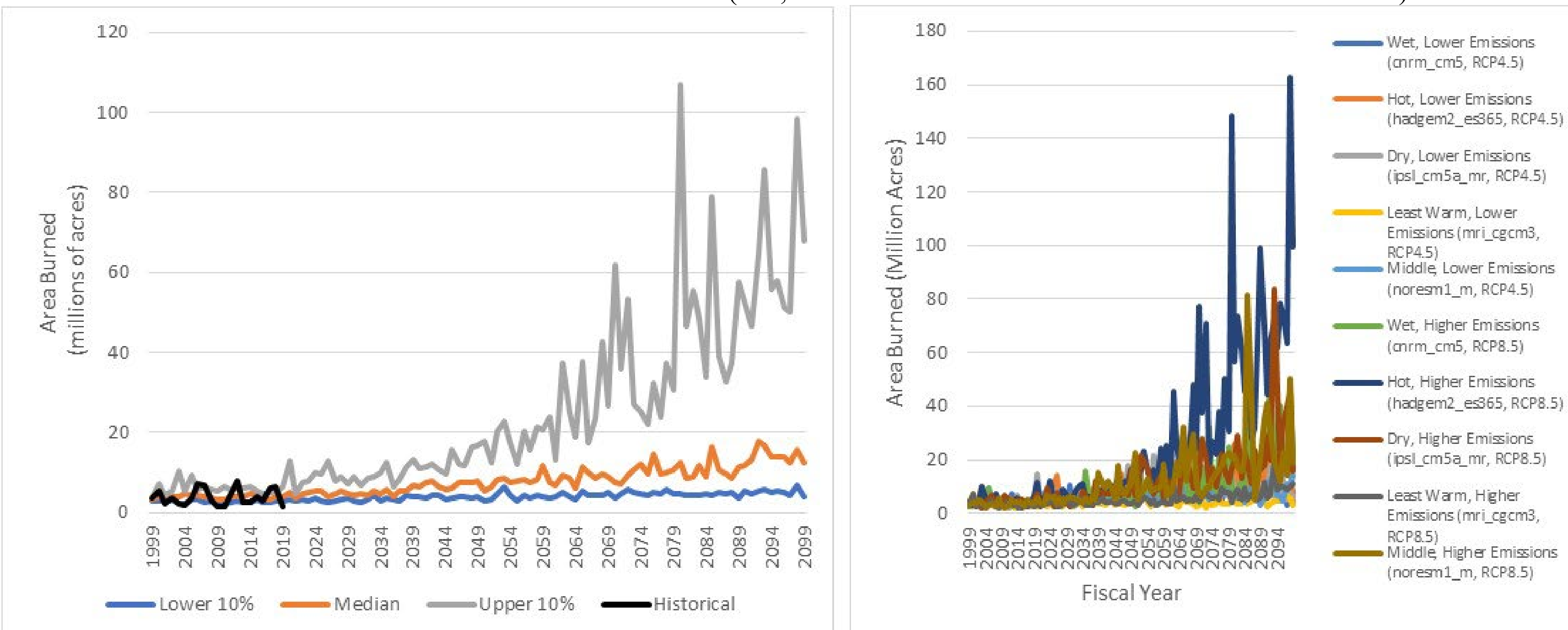


FIGURE 10: USDA FOREST SERVICE AREA BURNED, PROJECTED, BY FISCAL YEAR, ALL CLIMATE PROJECTIONS COMBINED, AND MEDIAN BY SCENARIO. MONTE CARLO 50 ITERATIONS PER GCM X RCP SCENARIO (I.E., 500 ITERATIONS INCLUDED IN THIS FIGURE).

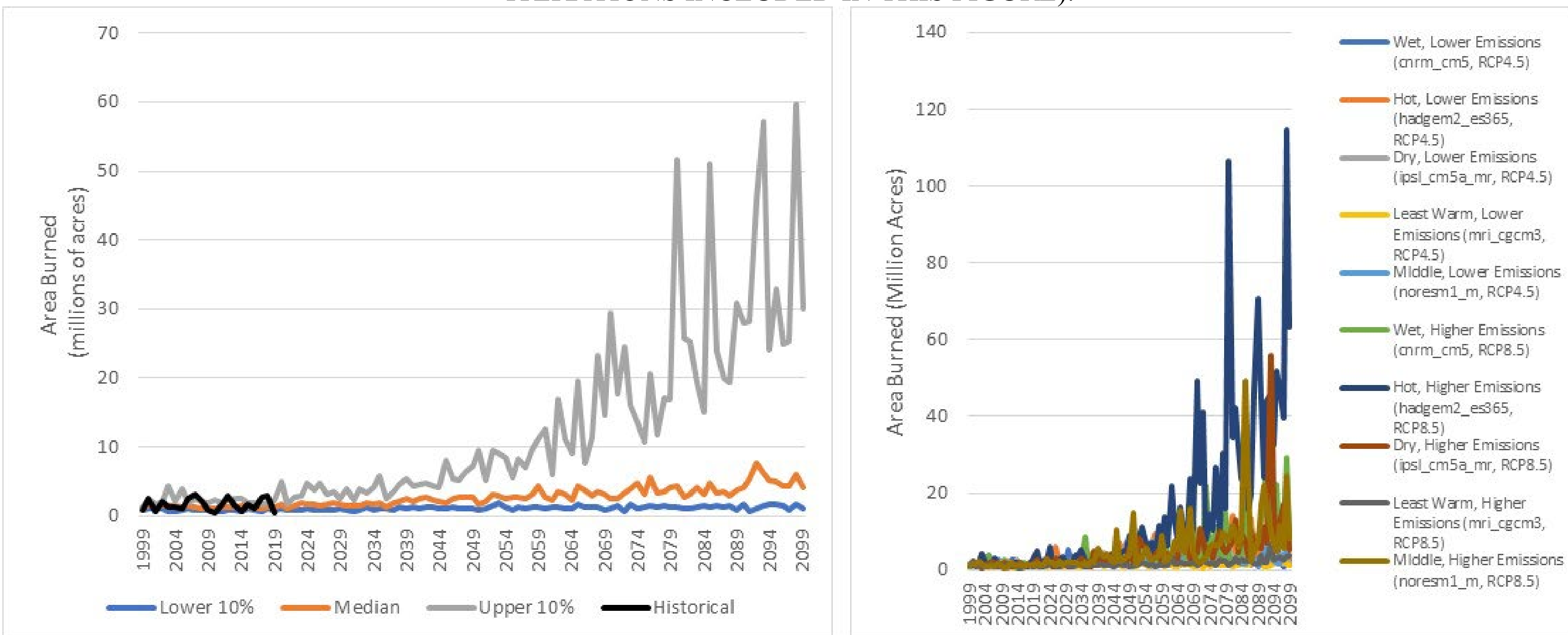
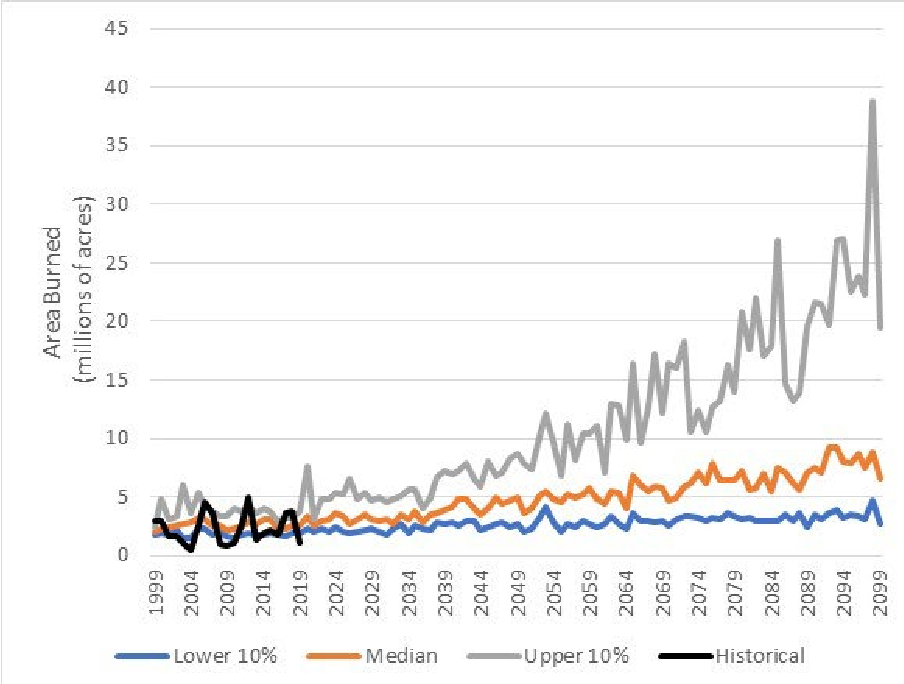
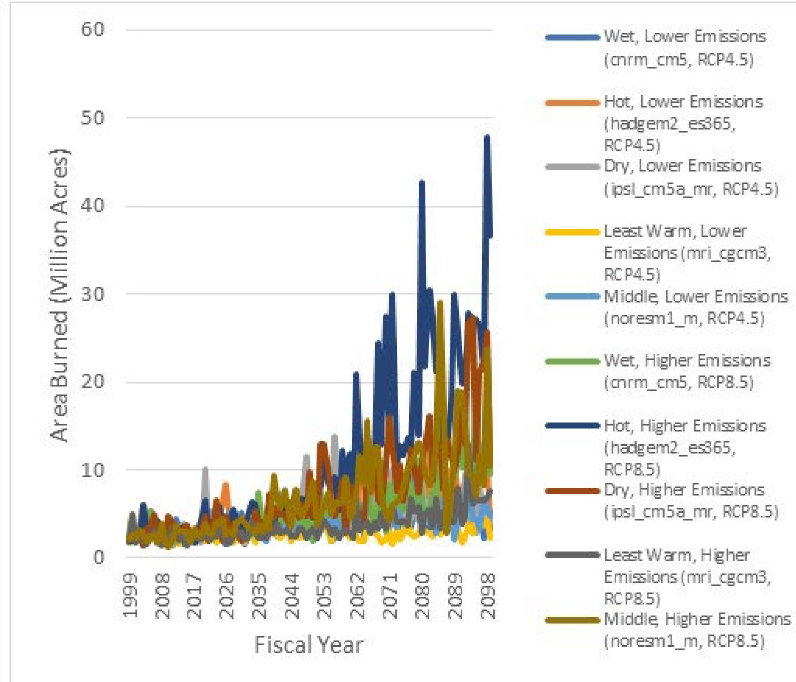


FIGURE 11: DEPARTMENT OF THE INTERIOR AREA BURNED, PROJECTED, BY FISCAL YEAR, ALL CLIMATE PROJECTIONS COMBINED, AND MEDIAN BY SCENARIO. MONTE CARLO 50 ITERATIONS PER GCM X RCP SCENARIO (I.E., 500 ITERATIONS INCLUDED IN THIS FIGURE).





Appendix C Table C.7 reports the Monte Carlo area burned projections numerically. This table is organized to show observed area burned over the benchmark years of 2013-2019, model projections of area burned over the benchmark years using backcast climate data from each of the GCM x RCP projections, and then projections of median area burned in mid-century (2041-2059) and late-century (2081-2099). The “All Scenario Median” and the 80 percent and 90 percent upper and lower confidence bounds reported are based on the combined 10 climate projections x 50 iterations/projection = 500 total iterations.

Appendix C Table C.7 shows the total of area burned projected for the FS and DOI and then combined. Broadly, the table shows general agreement between observed area burned for CONUS (3.77 million acres/year, 2013-2019) and backcast area burned for the same period (medians of the 10 climate projections range from 2.93-4.85 million acres/year) and a multi-scenario median of 3.96 million acres/year. When compared to backcast historical area burned, area burned in aggregate for FS + DOI is projected to be 13 percent to 167 percent higher by mid-century and 51 percent to 1,253 percent higher by late-century. The medians across all climate projections are 86 percent and 205 percent higher by mid- and late-century compared to modeled historical area burned (2013-2019)).

For FS CONUS lands, variability in total area burned is slightly larger than that projected for DOI. Just as for the FS + DOI in aggregate, there is wide variation across the ten climate projections for the FS, from an increase of 17 percent to 224 percent by mid-century and by 40 percent under the least-warm scenario with lower emissions to 2,134 percent by late-century under the hottest climate scenario (HadGEM2-ES365) with higher emissions. Across all ten climates for the FS, median area burned is 98 percent and 232 percent higher by mid- and late-century, respectively, compared to modeled historical area burned.

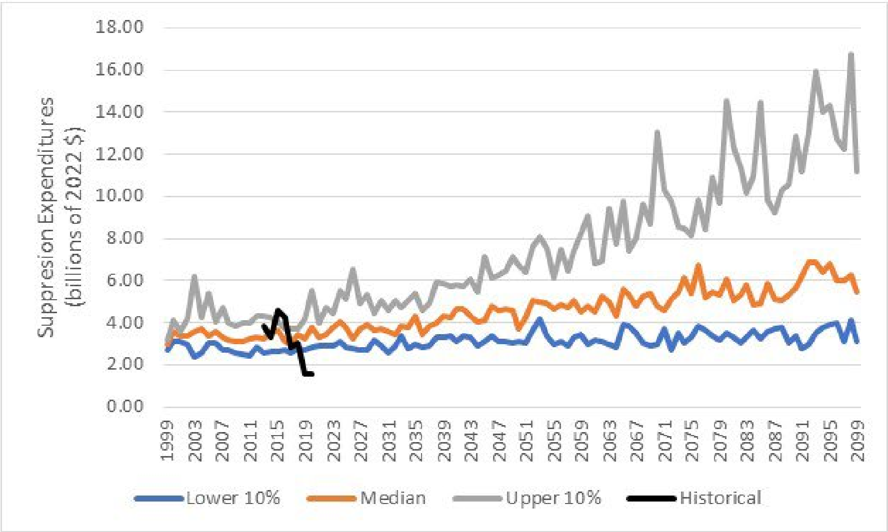
For DOI CONUS lands, there is wide variation across the ten climate projections, and overall, the projections demonstrate the same trends as reported for FS lands in CONUS. Compared to modeled historical (2013-2019), the area burned in CONUS on DOI lands is projected to be 77 percent and 171 percent higher by mid- and late-century, respectively.

It is notable that the median values for area burned, 2013-2019, using backcast climate (maximum temperature, VPD) variables (eighth column of values in Table C.7) reveal possible statistical biases produced by each of the climate projections (GCM x RCP scenario). Combined FS + DOI has slight positive overall bias when measured by the “all projections median” value (3.96 million acres/year) versus the observed value (3.77 million acres/year). For the FS, the backcast projections tend to under-predict in the 2013-2019 benchmark period (a median of 1.28 million acres/year backcast versus an average of 1.56 million acres/year observed), while the opposite is shown for DOI (2.63 million acres/year backcast versus 2.20 million acres/year observed). Because no climate projection can perfectly predict the backcast values of all climate variables, the lack of perfect alignment of median backcast predictions with the historical area burned is not unexpected, although modeling using some GCMs tend to predict lower and others higher than the observed area burned. For example, the “least warm” model (at RCP 4.5 and 8.5) predicts the lowest, while the “dry” and “hot” models (at 4.5 and 8.5) predict the highest in the 2013-2019 backcast for both FS and DOI. Those tendencies to predict low or high might in part explain the lower and upper ranges of projected area burned outcomes projected for mid- and late-century shown in the table.

Expenditure Projections

Graphs showing projections of expenditures are reported in Figure 12, Figure 13, and Figure 14. Just as for area burned, each figure has a left panel showing the median and 80 percent upper and lower bound projections of expenditures across all 10 climate projections, while the right panel in each shows the median projections for each of the 10 climate projections. Clear in all cases is that the high variability, particularly in late-century, in area burned is translated into high variability in projected expenditures.

FIGURE 12: TOTAL DEPARTMENT OF THE INTERIOR + USDA FOREST SERVICE SUPPRESSION EXPENDITURES, PROJECTED, BY FISCAL YEAR (INFLATION ADJUSTED 2022 DOLLARS), ALL CLIMATE PROJECTIONS COMBINED, AND MEDIAN BY SCENARIO. MONTE CARLO 50 ITERATIONS PER GCM X RCP SCENARIO (I.E., 500 ITERATIONS INCLUDED IN THIS FIGURE).



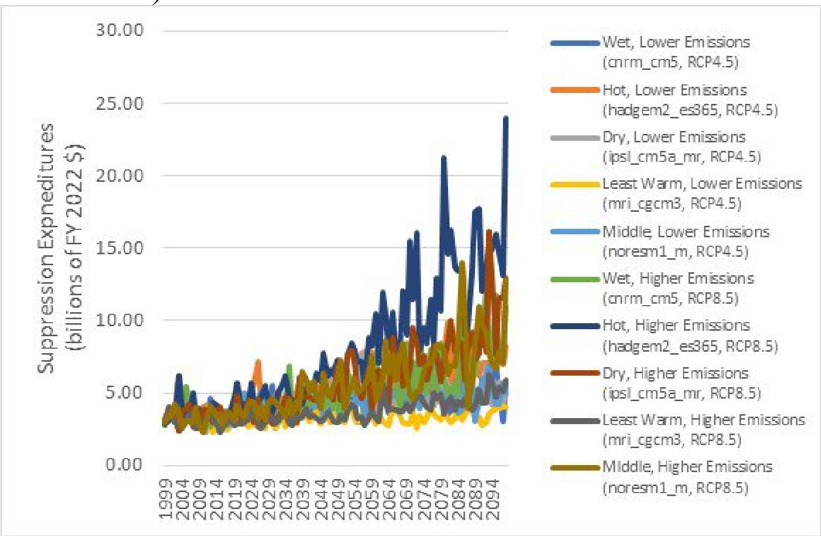


FIGURE 13: USDA FOREST SERVICE SUPPRESSION EXPENDITURES, PROJECTED, BY FISCAL YEAR (INFLATION ADJUSTED 2022 DOLLARS), ALL CLIMATE PROJECTIONS COMBINED, AND MEDIAN BY SCENARIO. MONTE CARLO 50 ITERATIONS PER GCM X RCP SCENARIO (I.E., 500 ITERATIONS INCLUDED IN THIS FIGURE).

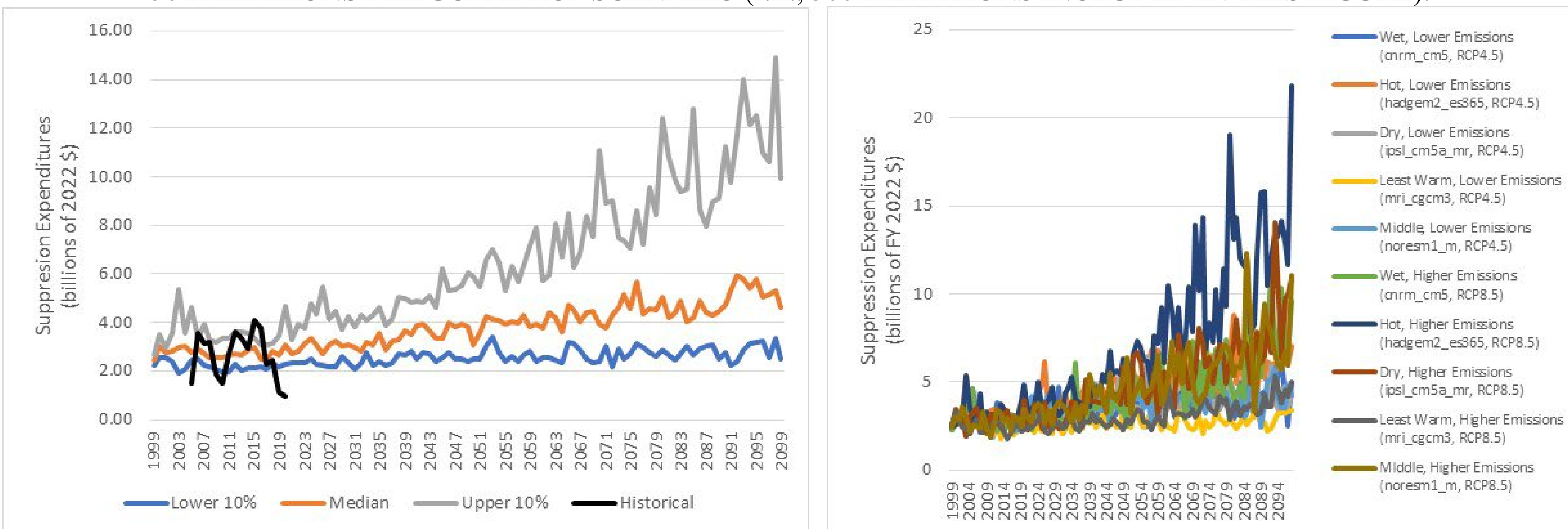
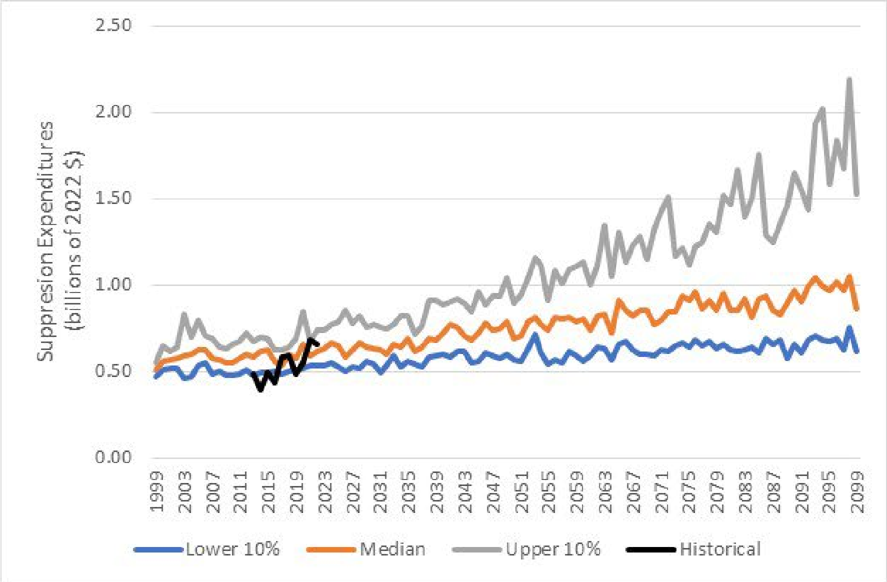
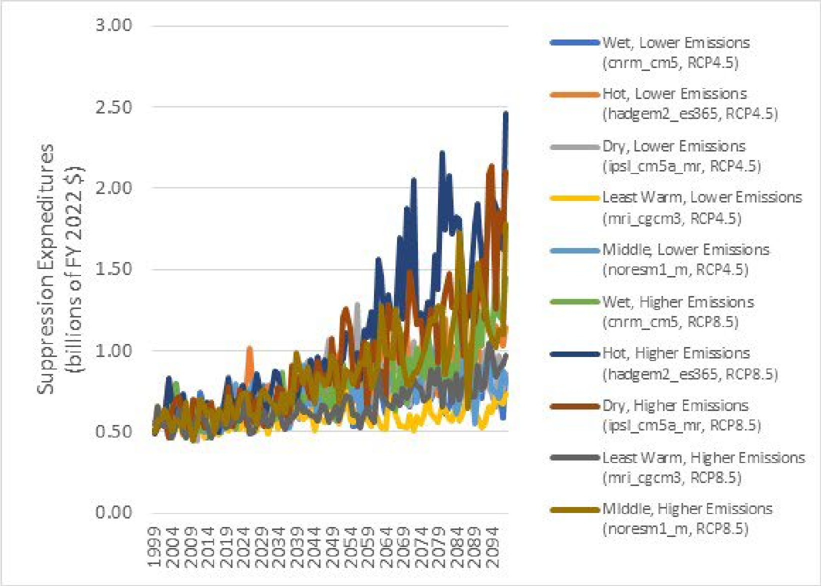


FIGURE 14 DEPARTMENT OF THE INTERIOR SUPPRESSION EXPENDITURES, PROJECTED, BY FISCAL YEAR (INFLATION ADJUSTED 2022 DOLLARS), ALL CLIMATE PROJECTIONS COMBINED, AND MEDIAN BY SCENARIO. MONTE CARLO 50 ITERATIONS PER GCM X RCP SCENARIO (I.E., 500 ITERATIONS INCLUDED IN THIS FIGURE).





Data from the graphs are summarized in Appendix C Table C.8. Data in the table are reported in the same way as for area burned projections, enabling comparisons between annual totals of expenditures observed and projected, except that the comparison years are narrower, due to more limited data availability of expenditures, in the benchmark historical period of 2013-2019. Like for area burned, the "All Scenario Median" and the 80 percent and 90 percent upper and lower confidence bounds reported are based on the combined 10 climate projections x 50 iterations/projection = 500 total iterations. As reported in Table C.8, in mid-century compared to modeled historical, median expenditures (in 2022 dollars) range from 13 percent higher to 79 percent higher, and for late-century 16 percent higher to 297 percent higher. In aggregate across FS + DOI, median projected real expenditures across all ten climate projections are 40 percent and 76 percent higher by mid- and late-century, respectively.

Appendix C Table C.8 documents how variability across projections in future expenditures is correlated with variability in area burned, but because expenditures were modeled as a function of sum of the square roots of area burned for each fire in each month in each spatial unit, the range of projected increases is substantially narrower. Across all climate projections, FS median suppression spending is projected to be 42 percent higher and 81 percent higher in mid- and late-century, respectively, when compared to modeled historical spending. Comparable figures for DOI (Table 3) are 31 percent and 58 percent higher in median suppression spending by mid- and late-century, respectively, when compared to modeled historical spending.

TABLE 3: SUPPRESSION EXPENDITURES (BILLIONS OF CONSTANT 2022 DOLLARS) BY FOREST SERVICE AND DEPARTMENT OF THE INTERIOR, HISTORICAL AND PROJECTED BY CLIMATE SCENARIO TO FY 2099 (MONTE CARLO AVERAGES AND MEDIANS).

				Fiscal Year					
	GCM Label	**GCM**	**RCP**	**2013-2019**	**2041-2059**	**2081-2099**	**2013-2019**	**2041-2059**	**2081-2099**
				Average Annual Expenditures (2022 Billion $)			Median Annual Expenditures (2022 Billion $)		
Forest Service	Wet	CNRM-CM5	4.5	2.87	3.40	4.29	2.91	3.32	4.15
Forest Service	Hot	HadGEM2-ES365	4.5	3.02	4.82	6.06	3.01	4.67	6.04
Forest Service	Dry	IPSL-CM5A-MR	4.5	2.71	3.96	3.93	2.68	3.70	3.78
Forest Service	Least Warm	MRI-CGCM3	4.5	2.43	2.81	2.86	2.41	2.74	2.82
Forest Service	Middle	NorESM1-M	4.5	2.69	3.81	4.27	2.62	3.69	4.33
Forest Service	Wet	CNRM-CM5	8.5	2.62	4.03	6.98	2.54	3.94	6.56
Forest Service	Hot	HadGEM2-ES365	8.5	3.17	5.84	13.14	3.06	5.70	12.91
Forest Service	Dry	IPSL-CM5A-MR	8.5	2.75	4.56	8.03	2.60	4.14	7.26

	GCM Label	GCM	RCP	Fiscal Year					
				2013-2019	**2041-2059**	**2081-2099**	**2013-2019**	**2041-2059**	**2081-2099**
				Average Annual Expenditures (2022 Billion $)			Median Annual Expenditures (2022 Billion $)		
Forest Service	Least Warm	MRI-CGCM3	8.5	2.32	2.76	3.96	2.28	2.72	3.79
Forest Service	Middle	NorESM1-M	8.5	2.80	4.64	7.11	2.85	4.51	6.63
Forest Service	All	All	All	2.74	4.06	6.06	*2.71*	*3.85*	*4.91*
Forest Service	All	All	*80% Lower Bound*	*2.60*	*3.78*	*5.43*	*2.16*	*2.58*	*2.81*
Forest Service	All	All	*80% Upper Bound*	*2.89*	*4.38*	*7.14*	*3.39*	*5.93*	*11.29*
Forest Service	All	All	*90% Lower Bound*	*2.54*	*3.69*	*4.41*	*2.01*	*2.40*	*2.34*
Forest Service	All	All	*90% Upper Bound*	*2.96*	*4.51*	*7.40*	*3.58*	*6.59*	*13.68*
Forest Service	Historical	Average (FY 2013-2019)		2.86					
DOI	Wet	CNRM-CM5	4.5	0.60	0.68	0.79	0.62	0.67	0.80

	GCM Label	GCM	RCP	Fiscal Year					
				2013-2019	**2041-2059**	**2081-2099**	**2013-2019**	**2041-2059**	**2081-2099**
				Average Annual Expenditures (2022 Billion $)			Median Annual Expenditures (2022 Billion $)		
DOI	Hot	HadGEM2-ES365	4.5	0.61	0.84	0.99	0.61	0.82	1.01
DOI	Dry	IPSL-CM5A-MR	4.5	0.58	0.80	0.80	0.58	0.77	0.78
DOI	Least Warm	MRI-CGCM3	4.5	0.54	0.61	0.63	0.54	0.60	0.63
DOI	Middle	NorESM1-M	4.5	0.57	0.75	0.80	0.56	0.73	0.80
DOI	Wet	CNRM-CM5	8.5	0.55	0.77	1.11	0.55	0.77	1.10
DOI	Hot	HadGEM2-ES365	8.5	0.62	0.93	1.78	0.62	0.92	1.75
DOI	Dry	IPSL-CM5A-MR	8.5	0.59	0.90	1.48	0.58	0.85	1.36
DOI	Least Warm	MRI-CGCM3	8.5	0.54	0.62	0.84	0.54	0.62	0.83
DOI	Middle	NorESM1-M	8.5	0.60	0.85	1.20	0.61	0.85	1.16
DOI	All	All	All	0.58	0.77	1.04	*0.58*	*0.76*	*0.92*
DOI	All	All	*80% Lower Bound*	*0.54*	*0.71*	*0.93*	*0.49*	*0.58*	*0.65*
DOI	All	All	*80% Upper Bound*	*0.62*	*0.84*	*1.14*	*0.67*	*0.98*	*1.62*
DOI	All	All	*90% Lower Bound*	*0.54*	*0.70*	*0.91*	*0.47*	*0.56*	*0.60*
DOI	All	All	*90% Upper Bound*	*0.63*	*0.84*	*1.14*	*0.69*	*1.07*	*1.89*

	GCM Label	GCM	RCP	Fiscal Year					
				2013-2019	**2041-2059**	**2081-2099**	**2013-2019**	**2041-2059**	**2081-2099**
				Average Annual Expenditures (2022 Billion $)			Median Annual Expenditures (2022 Billion $)		
DOI	Historical	Average (FY 2013-2019)		0.50					
FS + DOI	Wet	CNRM-CM5	4.5	3.47	4.09	5.08	3.54	4.00	4.96
FS + DOI	Hot	HadGEM2-ES365	4.5	3.63	5.65	7.04	3.60	5.50	7.05
FS + DOI	Dry	IPSL-CM5A-MR	4.5	3.30	4.75	4.72	3.27	4.44	4.55
FS + DOI	Least Warm	MRI-CGCM3	4.5	2.98	3.41	3.50	2.95	3.33	3.43
FS + DOI	Middle	NorESM1-M	4.5	3.26	4.56	5.08	3.19	4.39	5.15
FS + DOI	Wet	CNRM-CM5	8.5	3.18	4.80	8.08	3.07	4.72	7.66
FS + DOI	Hot	HadGEM2-ES365	8.5	3.78	6.77	14.83	3.69	6.60	14.64
FS + DOI	Dry	IPSL-CM5A-MR	8.5	3.34	5.45	9.47	3.17	4.99	8.59
FS + DOI	Least Warm	MRI-CGCM3	8.5	2.86	3.38	4.79	2.80	3.32	4.59
FS + DOI	Middle	NorESM1-M	8.5	3.41	5.49	8.30	3.47	5.38	7.79
FS + DOI	All	All	All	3.32	4.83	7.09	*3.30*	*4.62*	*5.81*
FS + DOI	All	All	*80% Lower Bound*	*3.17*	*4.56*	*6.48*	*2.67*	*3.16*	*3.45*

	GCM Label	GCM	RCP	Fiscal Year					
				2013-2019	**2041-2059**	**2081-2099**	**2013-2019**	**2041-2059**	**2081-2099**
				Average Annual Expenditures (2022 Billion $)			Median Annual Expenditures (2022 Billion $)		
FS + DOI	All	All	*80% Upper Bound*	*3.48*	*5.16*	*8.21*	*4.04*	*6.88*	*12.97*
FS + DOI	All	All	*90% Lower Bound*	*3.12*	*4.49*	*5.48*	*2.50*	*2.96*	*2.91*
FS + DOI	All	All	*90% Upper Bound*	*3.54*	*5.19*	*8.30*	*4.24*	*7.67*	*15.46*
FS + DOI	Historical	Average (FY 2013-2019)		3.35					

Discussion and Conclusions

The models developed here show that expenditures respond to changes in area burned as expected, and that area burned increases with increasing vapor pressure deficit and, in some cases, is additionally affected by average maximum temperature. Area burned is projected to increase by double or triple-digit percentages by mid- and late-century across most of the ten climate scenarios FS evaluated (Table 2). Real dollar suppression expenditures are projected to increase by smaller but still double-digit percentages by mid- and late-century.

While vapor pressure deficit and temperature are only two of several climate measures that have been linked to wildfire area burned, FS found that unbiased backcasts of area burned and expenditures could be obtained from parameterizing these simple relationships, and, in the case of the national forests, lagged area burned. However, model simplicity likely trades off with higher uncertainty in making projections, so definitive conclusions about the long-run status of wildfire and associated suppression on Federal lands in the U.S. may not be warranted without acknowledgment of these uncertainties. In the following section, FS details several reasons why uncertainty is large when envisioning the evolution of wildfire and expenditures.

Wildfire area burned and suppression spending display high uncertainty in their projected futures, particularly by late-century. FS notes that actual FS spending (and total FS + DOI spending), 2015-2019, twice exceeded even the 90 percent uncertainty upper bound modeled in this report, hinting that structural changes might be underway that will lead to spending that remains well above projected median levels for the foreseeable future. Additional modeling, perhaps directed at finer spatial scales and accounting more directly for hazardous fuels, could reduce uncertainties and help to reduce biases in model predictions. Nevertheless, it is possible that, even with improved models based on historical data, there will be structural changes in how fires burn under novel climates and novel vegetation assemblages, how fire managers apply suppression resources under shifting wildfire regimes, and in the real dollar unit costs of suppression resources over time. Such changes would imply that the projections reported here provide progressively less useful guidance, moving from mid- to late-century.

Caveats and Assumptions

The wildfire and suppression expenditure models used in this analysis involve several assumptions, violation of any of which would alter both the projected changes in spending and the ranges of our confidence bands. These assumptions, loosely grouped into aggregation bias (over space and time), omitted variable bias (including climate, fire, and socioeconomic variables) and modeling limitations, are discussed in more detail below. Even with these caveats and assumptions, however, these models, along with the literature FS has cited (and much that FS has not) provide evidence that both wildfire extent and suppression expenditures are expected to increase with climate change. The estimated models, specifically, show that vapor pressure deficit and temperature account for significant increases in area burned, that previous years' area burned is suppressive of current period wildfire, and that expenditures increase with increases in area burned and the square root of area burned.

Aggregation

The statistical models of area burned, square root of area burned, and of suppression spending are estimated using data aggregated from national forests or bureau-region aggregates to regions and bureaus and nationwide. Although models are refined in spatial resolution and account for differences in bureau lands and suppression spending in the current effort compared to previous efforts (2016, 2021-2022), remaining levels of aggregation, in the presence of heterogeneity in area burned and spending processes, would bias parameter estimates in undeterminable directions. Aggregation across space and time can interact with biases associated with omitted variables (next caveat), resulting in findings of insignificance when in fact significant effects exist (i.e., it can raise statistical Type II error rates). For both the FS and the DOI models of area burned, the fact that each region's area burn function was estimated separately allowed for the relationship between wildfire and climate to differ across regions and, through the panel structure, national forests. Even so, the assumption involved for the reported models is that fine-scale (finer than national forest or bureau-region spatial units) wildfire area burned responds to climate variables within that region. The FS models of the relationship between suppression spending area burned were also allowed to vary across national forests and across regions, but they still forced the spending-burn relationship (i.e., real dollars per square root of acres) to be constant within each region. For the DOI, because total bureau spending was modeled as a function of bureau area burned, the spending relationship to area burned implied constant spending per square root of acres. A similar forcing assumption was implied by non-regional spending of the FS and the DOI OWF.

Omitted variables

Statistical models of area burned, square root of area burned, and expenditures are parsimonious (i.e., they include only the most statistically significant variables to predict while limiting bias and imprecision), with area burned and square root of area burned specified as a function of monthly maximum daily temperature and vapor pressure deficit (and for national forests, up to five years of lagged areas burned). There is little doubt that potentially influential variables are omitted in the chosen specifications. Thus, these models assume that any omitted variables are orthogonal to the included variables, so that errors in projections are contained in error terms that are unrelated to the included variables. Alternatively, it could be that the omitted variables are perfectly correlated with the included variables, in which case parameter estimates for included variables completely contain the effects of the perfectly correlated omitted variables, and no bias would exist in resulting projections.

One key factor potentially missing from the suppression spending models is direct attention to human populations, which can lead to higher demands to protect property at the expense of area burned and which can affect the distributions of aggregate wildland fuels. Although FS tested for the relationship between spending and human population levels and changes and found inconsistent and usually non-significant effects, it is still possible that finer scale modeling of area burned and future population increase and more development in the WUI could warrant further consideration of population metrics in future modeling efforts.

Recent research has concluded both that temperature is a reasonable measure of climate change, but also that temperature is an insufficient measure of climate change influences on wildfire. In a statistical analysis of the relationship between meteorological variables and area burned in Canada, Flannigan and Harrington (1988) found that long sequences of days without rain, low relative humidity, and maximum temperatures were the best predictors of area burned, while rainfall and number of dry days per month were not significant. Romps et al. (2014) evaluated the impacts of climate change on lightning and found that (a) the precipitation projections do not show overall increases that would lead to increased lightning, and (b) increased temperature is the major controlling factor leading to increased lightning projections. Temperature has been shown to lead to a need for additional precipitation to hold fuel moistures constant (Flannigan et al., 2016). This results from the changes in the amount of water the air can hold at higher temperatures—as temperatures increase the air can hold more water, which leads to drying of fuels, even if precipitation stays the same. Flannigan et al. (2016) also conclude that increasing temperatures lead to an increased number of extreme fire weather days.

For these analyses, FS relied on mapping the association between temperature and vapor pressure deficit and area burned and square root of area burned into the future. However, the association between temperature and area burned has been demonstrated to be relatively weak in the absence of some form of a dryness metric (Littell et al., 2009). FS shows here only that temperature and vapor pressure deficit are significant, in the absence of other climate measures, in affecting area burned. The combination of VPD and maximum daily temperature in these models increased the goodness-of-fit out-of-sample compared to inclusion of these and other combinations of variables and also when those measures were excluded.

Many variables not included in the models for this study have been found in other research to affect both wildfire and suppression, so their omission means that they were assumed constant throughout the projections, even though it is unlikely that constancy will be maintained to the end of this century. Specifically, FS assumed that wildfire suppression strategies and technology do not change, and so FS did not need to include variables representing that change. FS assumed that suppression will not become more or less effective at limiting wildfire. FS assumed that wildland fuels management rates remain unchanged, in relation to overall wildfire activity. Research shows that management of aggregate fuels on landscapes can affect how wildfires burn, likely affecting suppression productivity and hence area burned or other damages upon which suppression is focused (Loudermilk et al., 2014, Mercer et al., 2005, 2007; Thompson et al., 2013). However, Bessie and Johnson (1995) compared the composite influences of fuels and climate and concluded that climate was the driving force in year over year changes in area burned. Nevertheless, the lack of direct statistical accounting for the effects of climate or management efforts to reduce hazardous fuels adds a degree of uncertainty to the projections that may not be reflected in the projections. Furthermore, models assume that allocations of suppression efforts across threatened people, property, and resources will be allocated in the same ways, in response to wildfire, as they have in the past. Because historical data on suppression spending and area burned reflect averages of policies to protect people, property, and resources, substantial changes in the ratios of these variables threatened by wildfires in the future could affect spending in ways not accounted for in the projections.

In this analysis, the general approach and structure of wildfire management was assumed constant over time. While this assumption was necessary for this analysis, long-term climate change's effects on wildfires and associated financial impacts may necessitate modification of human responses and new or alternative management approaches (that are not modeled here). Even within the near future (10 to 20 years) analyzed in the Quadrennial Fire Review (QFR) , there exists "a strong possibility that today's regional wildland fire management dynamics will shift as a result of climate and environmental factors." Furthermore, the QFR identified the potential for a shock-type wildfire event to instigate a fundamental realignment of Federal land and fire management functions that would clearly alter the relationship between area burned and management cost. It is doubtful that biologists and foresters in 1900 could have predicted the magnitude of wildfire sizes, behaviors, damages to human and natural resources, and costs experienced today, let alone the types of equipment used in suppression responses of today. Due to the increased uncertainty of both natural and human consequences of future climate, future management cost projections should be evaluated with caution.

FS also assumes constant socioeconomic variables, including relative prices, population, and income. If the per-unit cost of labor, capital, and other purchased inputs into suppression production were to rise at a rate higher than inflation, then suppression expenditures would tend to be higher, possibly also leading to lower overall suppression effort and then to greater square root of area burned. Generally, wages and capital costs have not been rising faster than inflation in the last 20 years. However, assuming the per-unit prices of the inputs into suppression production remain constant in real terms for multiple decades remains a strong assumption.

The projections indicate that, under some climate projections, area burned would increase over historical rates. As the projected annual area burned increases, however, this means that substantially more acres would need to reburn, or that wildfire would need to move into areas that historically have not burned, in order for these fires to have adequate fuel. In this current effort, FS has updated previous efforts' models to include lagged area burned on national forests (but not on DOI lands), which FS finds are generally negatively associated with current month wildfire. Hence, the new effort's wildfire area burned and square root of area burned variables reduce future wildfire, which, given this statistical association, is evidence that it accounts for the fuel treatment effects of wildfire. Because the DOI bureau-region models do not account even for recent historical wildfire, they could be prone to overestimation of the projected area burned, at least in forested landscapes (although, as shown in Appendix tables C.7 and C.8, the DOI wildfire area burned models and expenditure models tended to over-predict in the historical benchmark years, 2013-2019). Conversely, and in contrast to our model findings for national forests in this current report, in drier, range ecosystems, it is possible that increases in burning rates could lead to the potential for more fire, as reburning rates are expected to be higher in these ecosystems. For these ecosystems, particularly for DOI lands, our models would underestimate the projected area burned. It is not known at what burning rate these limiting conditions would be reached in either forest or range ecosystems. Hope et al. (2016) capped their Canadian area burned estimates assuming a 20-year fire return interval, equivalent to burning 5 percent of the wildland each year. Results suggest that by late-century, converting the median percentage changes from the modeled historical to an adjusted change that accounts for model biases, a median of 5.19 million FS acres per year could burn, or about 3.1 percent (but ranging from 1.1 to 36.11 million acres across scenario medians) of all FS land in CONUS. FS contends that FS had little justification for artificially capping area burned estimates, in the absence of a statistically modeled relationship. Additionally, because the United States has wide variation across ecoregions in wildfire return intervals (Greenberg & Collins 2021), simple solutions such as artificial caps would possibly add more uncertainty to projections, not less. It is possible that such relationships can be estimated, which would be an area worthy of additional study and modeling efforts.

Modeling

FS assumed that the included information from climate projections was adequate to capture uncertainty regarding the effects of temperature and vapor pressure deficit on area burned and square root of area burned on Federal lands. FS assumed that these systems could be approximated by an exponential relationship, with no significant biases or added uncertainty due to spatial autocorrelation and no significant effects of the assumption of mean-variance proportionality. More fundamentally, because our models could only be based on historical relationships among variables, FS assumed that those relationships would endure to the end of the century. The models make long-run projections, without evaluating which factors that are typically assumed fixed might be variable in the long-run, such as fire regimes, biomes, and suppression strategies. In addition, even at aggregate scales, the highly modified forest and grassland ecosystems of U.S. Federal lands may not bear much relation to either natural ecosystems or to ecosystems expected in the distant future under climate change (McKenzie and Littell, 2016).

Any model is an abstraction, a simplification of reality. In this analysis, FS used only five climate models under each of two RCP scenarios. Thus, FS assumed that five global climate model realizations of future climate under the increased radiative forcing of either $4.5W/m^2$ or of $8.5W/m^2$ were sufficient to capture the range of possible climate futures regarding vapor pressure deficit and temperature changes on Federal lands. FS did not assign likelihoods on whether either RCP was more likely than the other, nor did FS consider which GCM would best project the climate of fire prone federal lands. However, the five climate models allowed us to explore the wildfire and suppression spending implications of possible hot, warm, wet, and dry futures. The end of century projections by the Hadley model under RCP 8.5 portend hot temperatures and increased wildfire area burned. In contrast, the Least Warm model (MRI-CGCM3) projects the least change in area burned. While our Monte Carlo simulations address uncertainty in the estimated coefficients as well as uncertainty reflected in the multiple GCM temperature projections, FS did not incorporate any within-GCM uncertainty. The assumption here, and one that is widely accepted throughout the literature, is that the multiple models can proxy for uncertainty within the GCMs.

Uncertainty in wildfire projection exists even at the incident level, over the timeframe of hours to days, and is compounded when working at decadal or century-long scales (Riley & Thompson, 2016). One reason for compounding uncertainty is that shifts in vegetation assemblies and even biomes are likely during this timeframe due to climate change, meaning fire regimes will also shift (Lenihan et al., 2003, Loehman et al., 2014). Take, for example, the changes in fuels and vegetation documented since the turn of the 20th century (Loope & Gruell, 1973; Gruell, 1983; Gruell, 2001). By first removing Indian burning (Lewis, 1973; Barrett, 1980), and then attempting to remove wildfires, European settlement altered vegetation composition and structure, insect outbreaks, and wildfire behavior in just 100 years of relatively subtle climate changes. Feedbacks between shifting vegetation assemblies, changing climate, and altered ignition patterns will be complex and may produce no-analog states.

Caveat summary

Wildfire and fire management, including suppression, is a complex system where individual factors interact in complex, non-linear, and unpredictable ways. What happens in one component of the system will cascade through the system altering other components, and these cascades are multidirectional. Climate change is expected to influence ignition patterns, fire weather, ecological community composition, local community development, and the willingness and ability to manage wildfire. Each of these changes will reverberate through the system, adding uncertainty about the future of wildfire and suppression spending that may not be adequately captured by the simple statistical relationships that drive the results presented in this study.

2. Risks to Long-Term Infrastructure

The Federal portfolio of physical assets—buildings, infrastructure, and other fixed capital—are threatened by drastic changes in their local environment as a result of climate change. Importantly, and in contrast to privately owned capital, the Federal Government is financially responsible for any damages from natural disasters that occur to its own assets. This includes assets that are climate-sensitive, such as dams, irrigation infrastructure, and levees, where risk can come in the form of service reductions (e.g., flood mitigation) due to deviations away from the climate for which they were designed, such as an increased frequency and intensity of natural disasters (Financial Stability Oversight Council, 2021). Adding to the exposure of these physical assets is the fact that the built environment itself can be a major driver of climate change (Chu et al., 2023). For example, urban development patterns can exacerbate climate impacts, such as increases in heat capture and retention, and increases in the severity of flooding from overloaded stormwater infrastructure. An additional concern is that many of these risks are unevenly distributed across populations—often falling on already overburdened and historically marginalized communities. Recognizing this, the Federal Government has begun taking action to assess these risks and their impact on Federal fiscal responsibilities. This section provides additional details on two such efforts described in the AP chapter of the fiscal year 2025 budget: (1) an overview of ongoing assessments by the Department of Housing and Urban Development, and (2) a widespread accounting of the Department of Energy assets and infrastructure in the face of climate change.

U.S. Department of Housing and Urban Development: Commercial Loan Climate Risk Assessment Plans for 2026+

The U.S. Department of Housing and Urban Development's Federal Housing Administration (HUD FHA) insures single family and commercial portfolios of mortgages and seeks to proactively manage credit risk, including from current and future climate-related natural disasters. This includes managing the credit risk of FHA's multifamily and healthcare (collectively "commercial") loan portfolios, which, as of month-end August 2023, had nearly 15,000 loans totaling $162 billion in unpaid principal balances (UPB).[14] As part of HUD's response to Executive Order 14030, in partnership with OMB, HUD is taking action to improve its understanding and advance its capability to assess the physical risks of climate change to its commercial loan portfolios.

To better understand the effect of climate change on the multifamily and healthcare loan portfolios, and quantify these values for the public, HUD is developing several budget impact analyses in fiscal year 2024 to present in the fiscal year 2026 budget. Climate change poses several risks to HUD's commercial portfolio; most notably, buildings with chronic damage from coastal or riverine flooding, or acute damage from physical natural disasters, may experience reduced market values. When these borrowers default, whether due to economic causes or physical disasters, HUD's recoveries on lender claims will be lower, increasing the costs of these loan programs. The analyses described below will evaluate the degree to which FHA's commercial portfolios are at risk of climate-related impact and identify the dollar value of projected gains or losses.

Planned Analyses

HUD FHA's Office of Risk Management and Regulatory Affairs (Risk) regularly estimates the budgetary impacts of three commercial loan portfolios: 1) multifamily housing, 2) nursing home, assisted living, board and care, and 3) hospitals. For these calculations, Risk maintains financial models that forecast the probability of prepayment by the borrower, probability of insurance claim payment by FHA (due to borrower default), and probability of recovery on claimed loans/properties. These models allow Risk to produce reports for audits, budgets, portfolio management, and ad hoc policy analyses.

These models use a series of factors to forecast loan performance, including:

1. Loan characteristics (e.g., term, interest rates, etc.),
2. Borrower characteristics (e.g., default history, physical inspection score, etc.),
3. Borrower financial statements, and
4. Macroeconomic projections (e.g., vacancy rate, median household income, etc.)

These models undergo annual updates to incorporate the latest historical loan performance data and forecasted macroeconomic projections, as well as adjustments to the underlying methodology, if appropriate. These updates are evaluated and approved by HUD FHA's Model Risk Governance Board (MRG), overseen by the United States Office of Management and Budget, and audited by HUD's Office of Inspector General (OIG). Given the maturity and independent oversight of these models, HUD will use them as the starting point for the planned climate analyses.

Notably, these models do not include the impact of natural hazard risk, such as whether the property would be covered by hazard insurance, or the effects of climate change on natural hazard risk. Therefore, HUD proposes three novel analyses to incorporate physical climate risk into its

[14] Note, these multifamily and healthcare government loan programs are negative subsidy and therefore self-funded. Therefore, they do not require or receive annual appropriations from Congress.

models. This section provides additional detail on the three approaches for planned analyses described in the AP chapter of the Budget.

Approach 1: Simplified natural disaster cost calculation

The primary objective of this first approach is to incorporate physical natural disaster hazards into FHA's loan forecasting models and calculate the costs to FHA's commercial loan portfolios. FHA will use data from FEMA's National Risk Index to identify expected annual losses resulting from natural hazards. FEMA provides an annual loss rate for buildings by census tract, which FHA can incorporate into its models. The advantages of this approach include: (1) there is no cost to HUD, (2) data are widely accessible, and (3) data are easy to incorporate into FHA's existing models. However, there are several disadvantages, including: (1) the values do not reflect climate-induced risks, (2) the data are static, point-in-time values, limiting forecasting accuracy, and (3) the metrics are not targeted for FHA's insured commercial assets. Nevertheless, this methodology will allow HUD to calculate the costs of natural hazards on its commercial loan portfolio with vetted public dataset on an expedited timeline.

Approach 2: Historical loss data aggregation

In tandem with the baseline forecast in Approach 1, HUD plans to attribute historical claims and losses to historical natural disasters, consistent with standard econometric modeling techniques. This objective is notable as no comprehensive analysis of this type currently exists for FHA's commercial portfolio. HUD will aggregate records from Multifamily and Healthcare program offices on the financial damage due to hurricanes, fires, floods, wind, etc. This includes variables such as:

1. Loan and borrower characteristics
2. Reported losses and/or recoveries on sales of claimed assets
3. Insurance coverage and payments (federal, state, local)
4. Properties that claimed and those that were damaged, repaired, but did not claim

Similar to the first approach, this is an alternative method of establishing baseline costs due to natural disasters. While the first approach uses externally-derived assumptions, this method relies directly on realized FHA outcomes, which is more applicable than FEMA data because the assumptions are based on the same portfolio of assets. Overall, this approach has the following advantages: (1) assumptions are derived from FHA's portfolio of assets with the same credit quality, making the analysis quite pertinent, (2) data are readily available, and (3) FHA's team has robust experience calculating and applying assumptions using these data. However, there are disadvantages, including: (1) FHA has limited exposure to all historical natural disasters, while FEMA data reflect experience of all census tracts and historical disasters, (2) the assumptions will not account for climate change, and (3) the assumptions are not subject to the same level of scrutiny and review as FEMA's estimates. Nevertheless, this method allows HUD to incorporate bespoke, FHA-informed natural disaster indicators into the loan performance models to identify historical impact on defaults, prepayments, claims, etc. and calculate the costs of natural disasters historically and in the future.

Approach 3: Advanced forecast of budgetary impacts

Finally, FHA plans to develop an advanced budgetary forecast by incorporating robust climate data that is both spatial and temporal regarding transitional, chronic, and acute risks into its loan performance models.

Specifically, HUD will obtain: property-level climate risk data for probability of acute natural disasters, such as hurricanes, floods, and wildfires. Additionally, the Approach will incorporate time-varying macroeconomic forecasts on the transitional risks related to climate change. For example, at-risk coastal and flood prone areas may experience population reductions, which might reduce demand for multifamily and healthcare facilities, lowering revenues and increasing the probability of claims in those regions. Risk's loan performance models already incorporate many macroeconomic factors. Macroeconomic scenarios forecasting climate change's impact on unemployment rates, vacancy rates, and other factors will allow FHA to augment its models to obtain the budgetary impact of climate change, relative to the baseline runs described above.

This approach has multiple advantages compared to the prior approaches by allowing HUD to enhance its models via multiple factors. For example, the assumptions will adjust borrower behaviors, macroeconomic projections, and the physical impacts of climate-influence natural disasters. The aforementioned two analyses only assess the impact of physical natural disasters without explicit adjustments for climate change.

Subject to the availability of data, HUD plans to run a series of alternative scenarios, to capture more granular effects of climate changes, such as:

1. Analyze new cohorts of loans with greater climate exposure risk, due to adverse selection described in the literature.
2. Apply scenarios with varying increases in global temperature.
3. Apply scenarios with varying increases in sea level.
4. Adjust electricity usage/costs using the debt service coverage ratio calculations described in the literature.
5. Forecast estimates for future Fiscal Year (FY) cohorts (e.g., FY 2030 or later).

The purpose of these scenarios is to account for factors such as variation in climate change outcomes after 2050, anticipated changes to the portfolio composition based on external demand, and others. This approach has the following advantages: (1) uses assumptions tailored to comparable portfolios of assets, (2) uses assumptions that account for climate change influenced physical natural disasters, and (3) accounts for multiple aspects of climate change risk (transitional, chronic, and acute). There are disadvantages, however, including: (1) substantial cost to acquire data, (2) time to obtain data and learn how to use them, and (3) the complexity of the data requires trained staff to incorporate them into the model and run the results. Overall, however this method is a preferable approach, which will allow HUD to forecast defaults, prepayments, claims, and calculate the future costs of climate change.

Next Steps

With this plan, HUD is prepared to begin its analyses. The first step in the process has been ongoing for some time: obtaining access to the advanced forecast data identified in the third approach. While this step is in progress, HUD will begin preparing the two other analyses. HUD can apply the first approach's methodology immediately and begin analyzing the cost implications. At the same time, HUD will begin the data cleaning operations for the second approach. The data cleaning process to prepare the assumptions will take the most time. Once that is complete, it will not take substantial time to run the estimates in the existing models and calculate the costs. The first two analyses should take approximately 2-4 months to complete. Once these analyses are complete, HUD will present and vet the results internally and subsequently share with OMB's interagency working group.

Once HUD obtains the advanced spatially and temporally-relevant climate forecasting data, staff will clean the data, prepare it for use in the existing forecasting models, analyze the outputs, and interpret the results. These tasks will take approximately six months to complete, after the receipt of the data. Once the analyses are complete, HUD will undergo the same iterative feedback process as the two prior analyses. Based on the outcomes, including degree of success, HUD will identify which models are feasible to incorporate into its annual update process. HUD FHA's Risk team will regularly present results to the MRG, OMB, and OIG, along with the typical budgetary analyses provided annually. It is worth noting, however, that HUD will run the analyses that are feasible given the availability and appropriateness of the data. If, for any reason, the analyses are impractical, or if new techniques and data become available, plans may change. Nevertheless, this represents HUD's best opportunity to research and publish the potential impacts of climate change on the cost of its commercial mortgage portfolio.

U.S. Department of Energy: Managing Climate Risk at Department of Energy Sites

The Department of Energy (DOE) is committed to leading Federal efforts to manage the short- and long-term effects of climate change and extreme weather on its mission, policies, programs, and operations. In October 2021, DOE issued its Climate Adaptation and Resilience Plan (CARP) to meet the goals of Executive Order 14008: *Tackling the Climate Crisis at Home and Abroad*, and to make climate adaptation and resilience an essential element of the work DOE does. The CARP established an ambitious strategy to assess vulnerabilities and implement resilience solutions at DOE sites, which is the subject of this section.

In response to the CARP requirements, DOE established site-specific multi-disciplinary teams (VARP Teams) to develop Vulnerability Assessment and Resilience Plans (VARPs) to understand their individual site risks and the resilience actions necessary to mitigate the projected impacts of climate change. In this process, sites identified critical assets, analyzed historic climate events and damages, projected future climate hazards and associated risks, and developed sets of resilience solutions that respond to the identified risks.

Following the VARP process methodology as described in Figure 15, at each DOE site, a VARP Team was assembled to identify critical assets and infrastructure that are integral to their site's mission. The next step of the VARP process was for the team to identify regional climate hazards and forecast the projected impacts of these hazards on their critical assets and infrastructure. After identifying critical assets and projected climate trends, the teams used an Excel-based Risk

Assessment Tool to identify assets and infrastructure most at risk to climate change. Completion of this tool allowed the teams to identify and quantify their high-risk assets by calculating an asset's risk score to identify relevant hazards. The VARP Teams then began the resilience planning process by brainstorming solutions to address the identified vulnerabilities. After assessing expected effectiveness, cost, feasibility, implementation approach, environmental and community benefit, and priority rank, sites then selected the most appropriate solutions for inclusion in their resilience solution portfolio.

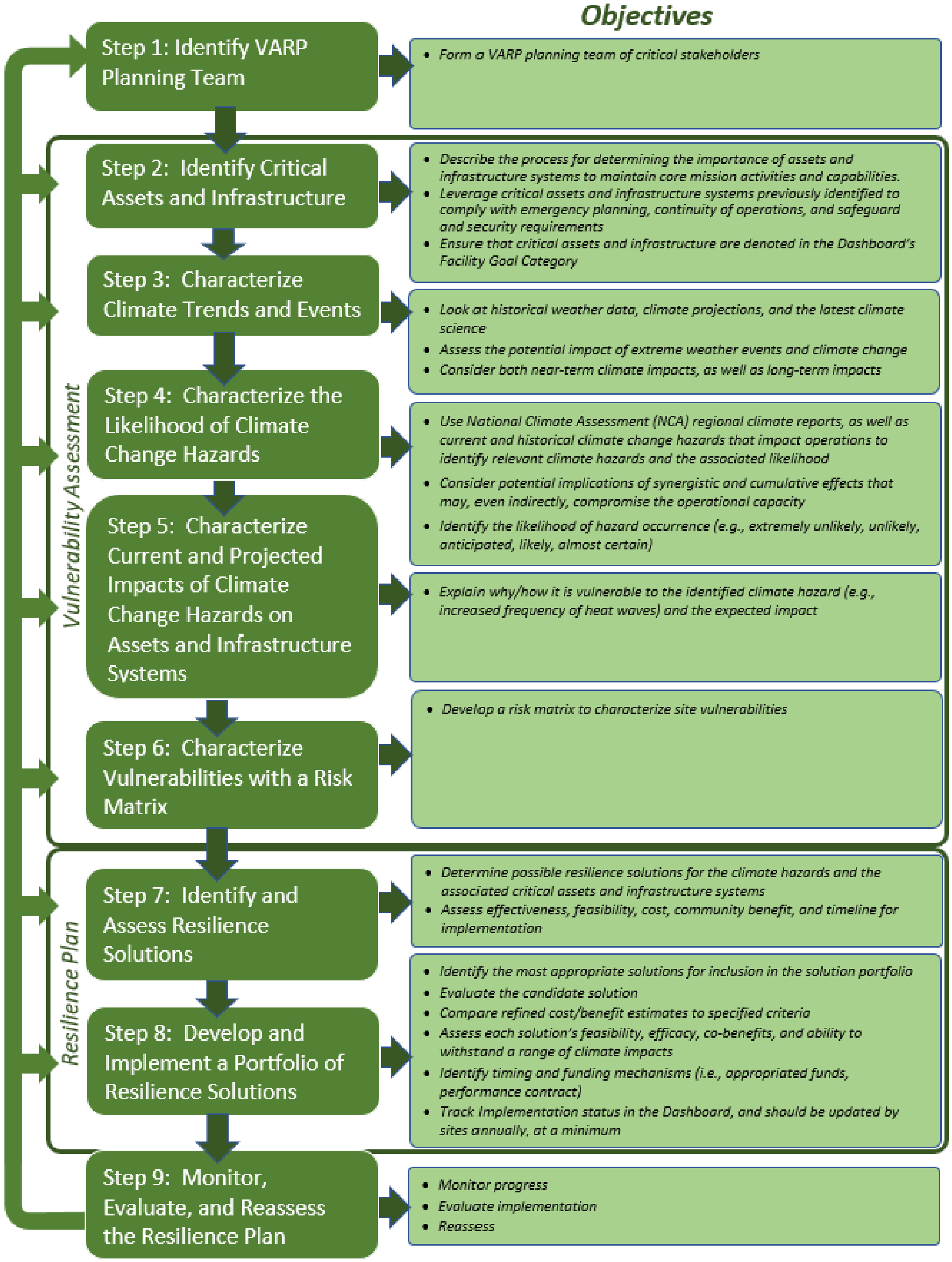
The DOE Office of Management's Sustainability Performance Office assessed the VARPs and developed an internal Department-wide summary analysis of historic climate impacts, projected climate hazards, regional trends, vulnerable critical asset categories, and proposed resilience solutions. The results of the VARP process indicate that DOE's assets most vulnerable to climate change are site buildings, mission critical equipment, and energy generation and distribution systems. The VARPs indicate that the climate risks posing the greatest risk to DOE operations, sites, and infrastructure are wildfires, heat waves, and extreme precipitation events.

DOE sites include a diversity of facilities and locations across the Nation, including 17 national laboratories, the nuclear weapons complex, the Environmental Management and Legacy Management sites, hydropower facilities, the Strategic Petroleum Reserve (SPR), and support offices. The sites are dispersed across the country—often in very remote areas—and are exposed to a wide range of climate impacts. Climate-related extreme weather events have been documented across the DOE complex for more than 20 years and based on site VARP projections are projected to increase in duration, frequency, and severity. Many of these events are projected to impact sites and increase response costs at an accelerating rate if action is not taken. While the 2022 site VARPs are not publicly available, examples of previous assessments are illustrated by the reports published by the National Renewable Energy Laboratory VARP and Resilience Action Plan. Other reports characterize the impacts of climate change and extreme weather as well as resilience solutions across the U.S., including:

- *Fifth National Climate Assessment:* Chapter 5. Energy Supply, Delivery and Demand (Zamuda et al., 2024)
- U.S. Energy Sector Vulnerabilities to Climate Change
- Regional Climate Vulnerabilities and Resilience Solutions

The financial impact of climate change on DOE has been significant. Since 2000, sites reported 31 separate events each costing the Department over $1 million, with an aggregated cost of $518 million. Facilities are vulnerable to a range of hazards, including extreme precipitation events, inland and coastal flooding, wildfires, and extreme temperatures. These major damages have impacted DOE's mission and affected a range of sites, facilities, and infrastructure. Climate hazards vary across the DOE locations. In 2011, a wildfire burned virtually unchecked in the Jemez Mountains near Los Alamos National Laboratory, and the fire's intensity and proximity to the Laboratory resulted in a 9-day closure for all non-essential personnel. The Las Conchas fire, the largest recorded wildfire in New Mexico history, burned 154,000 acres, including some Los Alamos National Laboratory land, and direct Laboratory damages were estimated at $15.7 million, not including lost productivity (Department of Energy, 2015). In September 2013, Los Alamos received 450 percent of average rainfall, leading to ground saturation. The unusually heavy precipitation event caused $17.4 million in damages to environmental restoration infrastructure, monitoring gages, roadways and storm water control structures on the National Laboratory property alone (*Ibid*.). In February 2015, severe winter weather, including an historic ice storm, hit the Y-12 National Security Complex in Tennessee. The storm caused significant damage to the facility, resulting in costs totaling $13.6 million (NOAA, 2015). The storm was characterized by freezing rain and ice accumulation, which caused widespread power outages and damage to infrastructure. Similarly, hurricanes along the Gulf Coast have cost sites over $50 million since 2008. The cost estimates provided in this section underestimate the total cost to DOE from climate change and extreme weather events. For example, in addition to physical damage costs, there are costs associated with lost productivity. For example, one site alone lost approximately 100 workdays to flooding, winter weather, and storms between 2013 and 2019. In addition, many smaller climate and extreme weather events have impacted DOE sites and incurred costs, but these and lost productivity costs are typically not monetized or reported, and are not reflected in the VARPs or summarized in this report.

FIGURE 15. PROCESS FLOW DEPICTING THE VULNERABILITY ASSESSMENT AND RESILIENCE PLANNING (VARP) STEPS AND ASSOCIATED OBJECTIVES



Incorporating Climate Risks in VARP Methodology

Climate and extreme weather risks and their trends are projected to vary on a regional basis. Figure 16 and Figure 17 below depict the most impactful risks to DOE sites by region and their most vulnerable assets, respectively.

FIGURE 16: CLIMATE AND EXTREME WEATHER RISKS PROJECTED TO POSE THE BIGGEST THREAT TO DOE SITES MOVING FORWARD, BY REGION

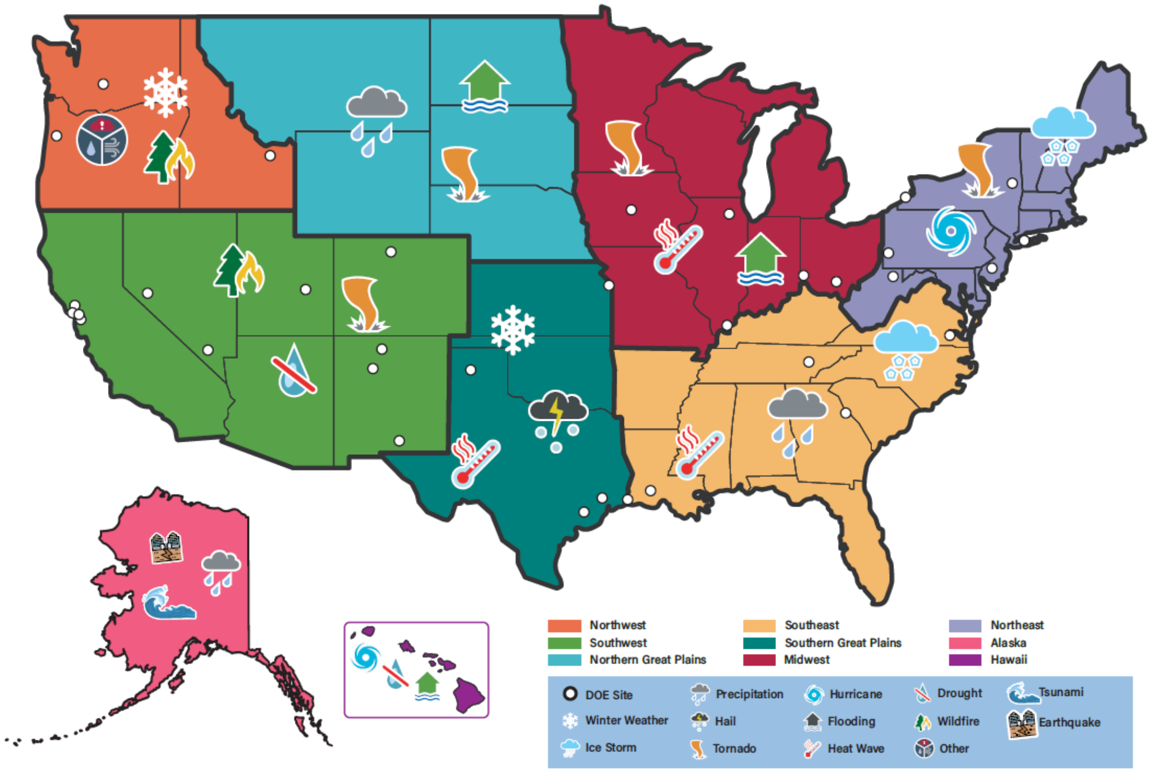


FIGURE 17: DOE ASSET CATEGORIES, PROJECTED TO BE MOST NEGATIVELY IMPACTED BY CLIMATE AND EXTREME WEATHER EVENTS MOVING FORWARD, BY REGION

As the figures indicate, the analysis identified many high-risk vulnerabilities across the Department. Some of the most vulnerable asset categories and impactful climate and extreme weather hazards are common across the DOE complex, while others are specific to a given region or site.

Climate-related hazards have already impacted assets and infrastructure at many sites and are projected to continue to increase in frequency, intensity, and duration. The Intergovernmental Panel on Climate Change (IPCC) establishes various modeling trajectories and pathways that help to quantify how hazards may change in the future. In conducting their VARPs, most DOE sites relied on the IPCC modeling and used Representative Concentration Pathways (RCP) 4.5 and 8.5 scenarios when characterizing the magnitude and likelihood of future climate hazards. These climate modeling scenarios represent low and high levels of GHG emissions, respectively, and the resulting effects on climate hazards are as follows:

- RCP 4.5: This scenario assumes that emissions are reduced compared to current levels; however, climate change is projected to cause significant impacts on DOE assets and infrastructure. For example, rising temperatures and changing precipitation patterns are expected to increase the frequency and/or severity of extreme weather events such as hurricanes, floods, and droughts.

- <u>RCP 8.5</u>: This scenario assumes that emissions continue to rise unabated with the result that the impacts of climate change on DOE assets and infrastructure will be even more severe. Warming temperatures, extreme weather events, and sea-level rise will all be more pronounced under this scenario, leading to even greater risks to DOE assets and operations.

Under both RCP scenarios, the question is not whether there will be future climate impacts on DOE sites, but rather how frequent and severe they will be, and how well-prepared the Department will be to mitigate or manage those risks. If sites can implement comprehensive sets of resilience solutions, they'll be able to minimize their risk exposure. For example, even though hurricanes may be considered a high climate hazard along the Gulf Coast, sites in this region indicated that hurricanes were not as threatening to their operations because they have implemented resilience solutions to reduce the risk of hurricane damages and operational impact.

Resilience Solution Identification and Implementation

To address their projected vulnerabilities, DOE sites identified resilience solutions in their VARPs. To aid sites in this, DOE partnered with the National Oceanic and Atmospheric Administration (NOAA) to provide technical assistance and access to a climate adaptation strategies tool, which provided actions grouped by hazard and asset. Table 4 provides examples of the types of resilience solutions identified.

TABLE 4: EXAMPLES OF RESILIENCE SOLUTIONS IDENTIFIED BY DOE SITES AND THE CLIMATE/EXTREME WEATHER HAZARD(S) THEY ADDRESS

Resilience Solution	Climate/Extreme Weather Hazard Addressed
Implement advanced cooling for transformers, cooling centers for workers	Heatwave
Install microgrid and battery storage infrastructure	Drought, Wildfire
Bury aboveground power lines	Strong Wind
Controlled burns and vegetation management	Wildfire
Reduce water use intensity, recycle water	Drought
Install seawalls, floodwalls, levees, or wetlands restoration	Riverine and Coastal Flooding, Tsunami
Install onsite renewable electricity generation and battery storage for backup power	All Hazards

For each solution, sites indicated which climate hazard(s) the solution would mitigate, as well has the expected effectiveness. Over 75 percent of solutions are expected to be effective or highly effective at mitigating their respective climate hazards. The remaining solutions are considered to either be somewhat effective or have an undefined level of effectiveness. In terms of implementation feasibility, 72 percent of the resilience solutions were identified to be easy or moderate. Sites also indicated the recommended timeframe for implementation, priority rank, and implementation status. The feasibility and expected effectiveness of solutions demonstrates that sites are aware of the risk posed by climate change on their operations and assets, and that they are actively identifying ways to effectively address these vulnerabilities in a timely manner.

Approximately half of the solutions are in the process of being implemented. The other half were not immediately planned for implementation because they were not prioritized, they require new technologies or equipment to mitigate climate change effectively and availability is limited. Other solutions were not planned because they were deemed technically infeasible, or the costs exceed the benefits. Additionally, gaps were identified in many resilience plans, meaning the proposed solutions did not comprehensively address the sites' climate vulnerabilities. Each region has specific high-risk vulnerabilities that currently lack resilience solutions. DOE will be identifying potential solutions for the identified gaps.

Further Advancing DOE Site Resilience and Needed Capabilities

DOE's resilience planning has taken a major step forward to increasing its understanding of the risks to mission and operations, as well as site resilience planning. The resilience solutions currently identified are a significant step forward for DOE, as many site-specific hazards, vulnerabilities, solutions, and implementation plans had not been previously characterized. When viewed in the context of the vast number of vulnerabilities that DOE sites face, however, it is clear that the identified measures, even if fully implemented, would not sufficiently mitigate the risks climate change poses. Going forward, DOE will seek to address these risks so sites can prioritize resilience investments by anticipated effectiveness, urgency, and return on investment.

In 2024, DOE plans to prioritize sites' identification of comprehensive solution sets, including prioritized implementation plans. DOE will assess the need for additional technical tools, support, and the sharing of best practices. Just as important, however, is the need to identify or create new tools that enable sites to model the financial costs and benefits and return-on-investment of various solutions. Such tools would enable sites to monetize and prioritize investments, and to compare and contrast the costs and benefits of investing in different types of resilience solutions versus taking no action.

To facilitate prioritizing the implementation of resilience solutions across sites, DOE is engaging in dialogue with its programs and sites about VARP implementation strategies, challenges, and best practices. For example, one DOE program has built a resilience and sustainability analysis into its project construction and renovation pre-design phase. The information will inform planning and design decisions, as well as to identify replicable best practices at the project level. Additionally, DOE is creating a new working group for sites and headquarters to share best practices and lessons learned, as well as to identify technical support and tool needs. Sustaining DOE's mission in this changing environment is dependent on DOE's ability to successfully identify aspects of climate change likely to impact the mission and operations, as well as our ability to find innovative and cost-effective ways to identify, fund, and implement resilience solutions to minimize further disruption and financial loss.

3. Social Safety Net and Human Health

Climate change directly affects valuable resources that are not traded in markets, such as ecosystem services, social safety nets, and human health (Hsiang et al., 2023). Climatic stressors have also been shown to increase racial segregation (Bakkensen & Ma, 2020), income inequality (Hsiang et al., 2019), and low-income communities' reliance on social safety net programs and credit systems (Roth Tran & Sheldon, 2019; Billings et al., 2022). In addition, rising temperatures, increases in the frequency and severity of extreme weather and wildfires, vector-borne diseases, food insecurity, and knowledge of the threat of climate change itself have all been linked to declines in Americans' physical and mental health (Carleton et al., 2022; Wen & Burke, 2022; Hayden et al., 2023). This section of the white paper provides additional information on the Environmental Protection Agency, Office of Land and Emergency Management's efforts to manage the impact of physical climatic risks on the remedy protectiveness and infrastructure of Superfund Sites.

U.S. Environmental Protection Agency: Managing Physical Risk at Superfund Sites

Additional Information on Vulnerability Assessment Methods and Climate Resilience Case Studies

In addition to national program guidance, EPA has described the processes and tools used to conduct climate vulnerability assessments at select Superfund sites and implemented adaptation measures to increase remedy resilience that help mitigate climate change. Two case study examples highlighted in the AP chapter that illustrate how climate adaptation is integrated into the Superfund program are expanded upon here. Further details from additional site profile case studies of climate adaptation at remediation sites—including the important roles and contributions from other federal partners are provided in the links below and at https://www.epa.gov/superfund/superfund-climate-resilience.

Rocky Mountain Arsenal Site Case Study

The Rocky Mountain Arsenal site in Commerce City, Colorado, is vulnerable to wildfires and the threats they pose to the site's existing infrastructure and buildings for system maintenance and groundwater treatment. The site is in the Wildland-Urban Interface, which implies additional risks of wildfires to surrounding communities. In December 2021, a wildfire quickly spread across more than 6,000 acres due to an unusually high amount of dry grass acting as fuel, a low amount of recent snowfall, and wind gusts exceeding 100 miles per hour.

In response to the identified remedy vulnerabilities to climate change and to adapt to these changing conditions, the site undergoes periodic prescribed burns conducted to expend potential wildfire fuels in a controlled a manner. This practice also helps maintain the desired perennial grasses providing habitat for native and migratory wildlife, prevents onsite growth of invasive plant species, and fosters local biodiversity. In addition, the reinjection of treated groundwater improves drought resilience, benefitting the community, and maintaining surface water levels at the site allows the U.S. Fish and Wildlife Service to stock the lakes with fish for recreation, fishing, and public space.

Port Hadlock Site Case Study

The Port Hadlock site borders Port Townsend Bay, a marine inlet in the Olympic Peninsula in Washington. Due to its coastal location, the covered landfill is vulnerable to erosion associated with tidal action and storm surge. EPA Region 10 site managers, in collaboration with Department of Defense partners, have responded to these risks through site inspections and remedy reviews which allow for more precise repairs to the landfill cap and armor rock replacement. In addition to addressing these risks, these resilience measures allow for shellfish rebound, proactive investments, and sustainable planning. Institutional controls involving restricted site access and land use remain in place.

Further Advances in Climate Adaptation and Climate Risk Management at Remediation Sites

As a priority action in fiscal year 2024 and fiscal year 2025, OLEM will focus on deploying assessments for communities located near contaminated or waste management sites, municipal waste management facilities or waste recycling facilities, where there are identified climate vulnerabilities.

Communities with potential environmental justice concerns may require additional engagement and resources to evaluate and address climate vulnerabilities they may face related to the proximity of areas such as chemical facilities, contaminated sites, waste management facilities, and oil facilities.

Vulnerabilities that will be addressed through these activities include:

- Restoring Land
- Emergency Response
- Municipal Waste and Materials
- Vulnerable Communities
- State Grants and Program Funding

These activities will be conducted in fiscal year 2024 and fiscal year 2025. Fiscal year 2024 activities will focus on development of a draft climate vulnerability assessment issue paper, and OLEM's climate assessments will be integrated into 4 site-specific programmatic activities. In fiscal year 2025, OLEM will finalize the climate vulnerability assessment issue paper and climate assessments will be integrated into 8 site-specific programmatic activities.

4. National Security

Climate change exacerbates many national security risks that affect a range of U.S. domestic and international interests. These risks contribute to political and social instability and can also affect the operations and missions of defense operations at home and worldwide. Similar to the effects of stressors and risks posed to domestic sectors and operations, such as agriculture and preparing the built environment for climate change impacts, these same risks have national security implications. Adaptation and mitigation actions, and underlying governance structures to implement these actions, contribute to how significantly climate change risks affect national security interests (Helmuth et al., 2023). Federal agencies have been taking action for years in recognition of these risks and have developed a sophisticated ecosystem of expertise, protocols, and decision frameworks to assess and address identified climate risks. This section provides a highlight from the Department of Defense on the policy, programs, and analytical capabilities currently being implemented to respond to national security risks posed by current and future climate change impacts.

U.S. Department of Defense: Managing Climate Risks at Department of Defense Sites

This section of the white paper expands upon the discussion presented in the AP chapter.

Introduction

Climate change is adversely affecting the U.S. Department of Defense's (DOD's) national security-related missions and operations by amplifying operational demands on the force, degrading installations and infrastructure, and increasing health risks to service members. The risks of climate change to DOD strategies, plans, capabilities, missions, and equipment, as well as those of U.S. allies and partners, are growing.[15] DOD has been forced to absorb billions of dollars in recovery costs from extreme weather events typical of those fueled by climate change. This includes: $1 billion to rebuild Offutt Air Force Base, Nebraska after historic floods; $3 billion to rebuild Camp Lejeune, North Carolina after Hurricane Florence; and $5 billion to rebuild Tyndall Air Force Base, Florida after Hurricane Michael. Most recently, estimates show that an extreme precipitation event at the U.S. Military Academy, West Point, NY in July 2023 caused more than $200 million in damages.

DOD is responding to climate change with myriad policy and planning efforts to reduce risk to national security. DOD's predominant approaches are adaptation to enhance resilience to the effects of climate change by reducing DOD's operational and installation energy demand. DOD's existing policy for adaptation and resilience dates to the release of the DOD 2014 *Climate Change Adaptation Roadmap* and the establishment of DOD Directive (DODD) 4715.21, *Climate Change Adaptation and Resilience*, in 2016. DODD 4715.21 (updated 2018) establishes policy and assigns responsibilities to provide the DOD with the resources necessary to assess and manage risks associated with the impacts of climate change. This involves deliberate preparation, close cooperation, and coordinated planning by the DOD to:

- Facilitate Federal, state, local, Tribal, private sector, and nonprofit sector efforts to improve climate preparedness and resilience, and to implement the 2014 DOD *Climate Change Adaptation Roadmap* and its successor 2021 *DOD Climate Change Adaptation Plan*,
- Help safeguard U.S. economic, infrastructure, environment, and natural resources, and
- Provide for the continuity of DOD operations, services, and programs.

DOD climate resilience also addresses energy and water resilience, both of which can be adversely impacted by extreme weather and climate change, generally contained in DODD 4180.01, *DOD Energy Policy*, and DOD Instruction (DODI) 4170.11, *Installation Energy Management*. A new

[15] Department of Defense, Office of the Undersecretary for Policy (Strategy, Plans, and Capabilities). (2021). Department of Defense Climate Risk Analysis. Report Submitted to National Security Council. https://media.defense.gov/2021/Oct/21/2002877353/-1/-1/0/DOD-CLIMATE-RISK-ANALYSIS-FINAL.PDF

DODI, *Integrated Installation Resilience*, is in process. This Instruction identifies 27 DOD issuances and 8 memoranda that are in the process of or will require further updating. The Military DOD Agencies also issue specific policies and memoranda. DOD policy and technical guidance updates are addressing numerous Title 10 statutory requirements related to climate, water, and energy resilience, including the following:

- 10 USC 101, Definitions
- 10 USC 1791, Office of Family Readiness Policy
- 10 USC 2224, Defense Information Assurance Program
- 10 USC 2285, Department of Defense Climate Resilience Infrastructure Initiative 10 USC 2391, Military base reuse studies and community planning assistance
- 10 USC 2667, Leases: non-excess property of military departments and Defense Agencies
- 10 USC 2679, Installation Support Services: intergovernmental support agreements
- 10 USC 2684, Cooperative agreements for management of cultural resources at military installations
- 10 USC 2687, Base Closures and Realignment.
- 10 USC 2691, Restoration of land used by permit or damaged by mishap, reimbursement of state costs of fighting wildland fires
- 10 USC 2692, Storage, treatment, and disposal of nondefense toxic and hazardous materials
- 10 USC 2694, Conveyance of surplus real property for natural resource conservation 10 USC 2802, Military construction projects
- 10 USC 2815, Military installation resilience projects
- 10 USC 2816, Consideration of energy security and energy resilience in life-cycle costs for military construction
- 10 USC 2864, Master plans for major military installations
- 10 USC 2866, Water conservation at military installations
- 10 USC 2911, Energy policy of the Department of Defense
- 10 USC 2915, Use of renewable forms of energy and energy efficient products
- 10 USC 2919, Department of Defense participation in programs for management of energy demand or reduction of energy use during peak periods
- 10 USC 2920, Energy resilience and energy security measures on military installations 10 USC 2925, Annual Department of Defense Energy Management Report

Climate Adaptation to Enhance National Security Resilience: The financial and national security consequences of failing to adapt to climate change will only compound over time, due to lost military capability, weakened alliances, weakened international stature, degraded infrastructure, and missed opportunities for technical innovation and economic growth. Since the release of the DOD 2014 *Climate Change Adaptation Roadmap*, DOD policy has required that all operations, planning activities, business processes, and resource allocation decisions include climate change considerations. The purpose of doing so is to ensure the military forces of the U.S. retain operational advantage under all conditions, leveraging efficiency and resilience to ensure our forces are agile, capable, and effective. Climate change adaptation must align with and support the Department's warfighting requirements.

The DOD climate adaptation framework for current and future force decisions laid out in the 2021 *DOD Climate Adaptation Plan* provides an update to the 2014 *Roadmap* and has five major lines of effort (LOEs): (1) Climate-Informed Decision-Making, (2) Train and Equip a Climate-Ready Force, (3) Resilient Built and Natural Infrastructure, (4) Supply Chain Resilience and Innovation, and (5) Enhance Adaptation and Resilience Through Collaboration. Four enablers support and integrate these LOEs: continuous monitoring and data analytics, aligning incentives to reward innovation, climate literacy, and environmental justice.

All actions in the DOD Climate Adaptation Plan are dependent on the outcomes of LOE 1, Climate-Informed Decision-Making. Climate considerations must continue becoming an integral element of DOD's enterprise-wide resource allocation and operational decision-making processes. Climate assessments must be based on the best available, validated, and actionable climate science that informs the most likely climate change outcomes. Climate data sources must be continuously monitored and updated—with consideration of the operational impact—to account for the rapid rate of climate change and its impacts. Examples of assets supporting Climate-Informed Decision-Making include the DOD Climate Assessment Tool (DCAT), DOD Regionalized Sea Level Database, and the issuance of guidance on climate parameters for wargames.

The AP chapter provides a discussion of the *DCAT.* This section provides additional examples of DOD climate adaptation tools.

DOD Regionalized Sea Level (DRSL) Database: DRSL provides regionalized sea level scenarios for three future time horizons (2035, 2065, and 2100) for 1,774 DoD sites worldwide, supporting climate-resilient coastal installation and facilities planning. Developed in 2016 with the assistance of an interagency working group, DRSL provides sea-level change trends and extreme total water levels. In 2021, the public release of DRSL extended database availability to contracted third parties such as engineers and architects. DoD facilities standards now incorporate DRSL information in planning and design (e.g., Unified Facilities Criteria (UFC) UFC 2-100-01 Installation Master Planning, with Change 1 and UFC 3-201-01, Civil Engineering).

Climate Exposure Data Supporting Decision-Making: Climate exposure information from DCAT is required for the Energy Conservation and Resilience Investment Program, to enhance energy and water resilience while accounting for changing climate (e.g., increasing high heat days, drought) and avoiding exposure when possible (e.g., wildfire, flood inundation). The DoD Legacy Resource Management Program included a fiscal year 2023 Nature-Based Solutions (NBS) program to assist installations in identifying NBS to reduce the impacts of extreme weather and climate change. Likewise, the Readiness and Environmental Protection Integration (REPI) Program funds off-base nature-based solutions, also known as REPI Installation Resilience Projects, to reduce the effects of extreme weather and climate change on DoD testing and training lands, infrastructure, and community facilities that safeguard military missions. The Office of Local Defense Community Cooperation awards installation resilience grants across the country to address resilience and encroachment risks and impacts and assist installations with optimizing their missions. Geographic information system (GIS) crosswalks of climate exposure and the presence of Environmental Justice Communities per the Council on Environmental Quality's Climate and Economic Justice Screening Tool assist in understanding installation and community resilience.

Partner Nation Climate Assessment Tools (CATs): In April 2021, the Secretary of Defense committed to producing custom, stand-alone versions of DCAT for partner nations (PN). The objective was to support climate exposure assessments for their defense agencies and enhance PN climate risk management. This in turn strengthens U.S. national security and enhances U.S. resilience against climate change. Three CATs are located in the European Command and three in the Indo-Pacific Command areas of responsibility. The CATs use global authoritative information about past extreme weather events (e.g., tropical cyclones) and projected sea levels, riverine flooding, drought, extreme temperature, land degradation, energy demand, and wildfires to produce hazard indicators and aggregated scores. The PN CATs help to identify salient climate/financial risk management practices before extreme events occur, reducing the resources required to respond, recover, and repair from climate-related damages at home and abroad.

Energy Demand Reduction to Enhance National Security Resilience*:* Reducing energy demand is critical to enhancing operational capability and limiting agency exposure to climate risk and to reduce the potential for unmanageable climate change effects on military operations. Reducing energy demand accelerates the Department's ability to limit risks in scenarios driven by extreme weather and enemy forces in tandem.

DoD Plan to Reduce GHG Emissions: Efforts set forth in the DoD Plan to Reduce GHG Emissions—reducing operational and installation energy demand, using distributed, alternative energy supplies and pursuing technology innovation—will help reduce climate risk in contested environments, enhance operational flexibility, bolster supply chains, and improve installation resilience, while also reducing GHG emissions. Through these initiatives and investments, the Department is making important progress toward the Federal Government's goal of a net-zero economy by mid-century.

A Joint Force that reduces the energy (typically energy-dense petroleum-based fuels) to execute its missions can reduce the risks associated with deploying, employing, and sustaining Joint Forces in contested operating environments. The ability to operate for extended periods, over long distances, with greater speed and payload, or in more locations directly increases DoD's capability and reduces an adversary's ability to disrupt the provision of energy for sustained operations. For example, improving efficiency and deploying clean distributed generation and storage can strengthen the resilience of critical missions housed on military installations in the face of extreme weather, cyber-attacks, and even kinetic attacks impacting electric grids. DoD will reduce operational energy demand by improving the efficiency of existing platforms; acquiring new, more energy-efficient replacement platforms; and adapting operational practices and procedures. Planned efforts related to installation energy demand reduction include improving data availability, reducing gross facility footprint (square footage), and introducing efficiency upgrades.

5. New Analytical Capabilities

As demonstrated in each of the prior sections' assessments and program highlights, each agency required the use of or developed customized analytical capabilities that provided spatially relevant projections of physical climate change impacts. These same analytical capabilities are needed by a range of stakeholders; for example, by architects and engineers that are designing built environment projects to account for future climate change and extreme weather impacts, farmers and ranchers adjusting operations and incorporating climate-smart agriculture practices, and municipal government officials that are incorporating climate risks in updates to their general plans. As described in the National Climate Resilience Framework, the Federal Government has published and is updating a range of analytical tools, such as the Climate Mapping for Resilience and Adaptation portal, the Sea Level Rise Viewer, and the Climate and Economic Justice Screening Tool. Additionally, agencies are working to incorporate these types of tools to aid applicants with financial assistance opportunities and in Federal real property management, and agencies have outlined steps to advance actionable climate services in the Federal Framework and Action Plan for Climate Services. This section builds on these recent announcements with highlights of newly published analytical capabilities from FEMA and new tools published alongside NCA5.

Climate Risk Analytical Tools from the U.S. Federal Emergency Management Agency

This section provides an expanded discussion of the Climate Risk and Resilience Portal (ClimRR), Resilience Analysis and Planning Tool (RAPT), and the FEMA National Risk Index (NRI) and Climate Informed Risk Index tools that are presented in the AP chapter of the President's Budget, and includes two case studies of how these decision support tools have supported state-level hazard mitigation planning and cooling center siting.

Climate Risk and Resilience Portal (ClimRR)

ClimRR provides free, equitable access to leading, peer-reviewed dynamical downscaled climate datasets to support analysis and data-driven planning for future climate risks. ClimRR hazards include maximum and minimum temperature, cooling and heating degree days, heat index, precipitation/lack of precipitation, wind speed, and fire weather index downscaled to 12 km grid cells for CONUS and most of Alaska. All data are available for two possible future warming scenarios (RCP8.5 and RCP4.5) and three time periods (historical, mid-century (2045-2054), and end of century (2085-2094)). In 2024, ClimRR will include new projection data for coastal and inland flooding, available for 200m grid cells and displayed by hydrologic unit code (HUC) 12 watersheds. In 2024-2025, ClimRR will begin to incorporate datasets downscaled to 4 km for CONUS, all of Alaska and Puerto Rico. ClimRR also includes selected community and infrastructure data layers. ClimRR data are produced through a public-private collaboration between FEMA, Argonne National Laboratory, AT&T, and the Department of Energy's Grid Deployment Office.

The datasets underling ClimRR were created using dynamical downscaling through a process that uses a simulated, physical model of the Earth, incorporating over 60 unique climate variables progressed in time every forty seconds, with data saved every three hours. Simulations were run for a decade each over historical, mid-century, and end-of-century time periods. Dynamical downscaling explores interactive climate mechanisms and requires millions of computational hours only achievable with a supercomputer. In addition, dynamical downscaling can provide physics-based climate projections for complex climate conditions not possible with more common statistical downscaling, including coastal flooding (as input for the Advanced Circulation Model), heat index, fire weather index, and vapor pressure deficit (drought). ClimRR's dynamical downscaled data gives the public access to one of the most robust understandings of how and where climate is changing at a local level.

ClimRR data are available as GIS data layers, both for direct interaction through the ClimRR online portal and as stand-alone datasets for download and use from the portal. ClimRR data combined with the population and infrastructure data in RAPT can be used to help jurisdictions incorporate climate projections into Hazard Mitigation Plans, assess infrastructure design criteria, and support land use planning. FEMA is also examining how ClimRR data can be integrated into Benefit-Cost Analysis for mitigation projects and can be used to update Hazard Mitigation Plans, assess infrastructure design criteria, and support land use planning.

Resilience Analysis & Planning Tool (RAPT)

The Resilience Analysis & Planning Tool (RAPT) is designed to give everyone access to a free, browser-based GIS tool to examine the interplay of population demographics, infrastructure and hazards, weather and risk. RAPT includes over 100 pre-loaded data layers and easy-to-use analysis tools for data-driven decision making for all phases of emergency management. RAPT includes the FEMA Community Resilience Challenges Index (CRCI), a composite index of 22 indicators used in multiple peer-reviewed research methodologies. RAPT includes the FEMA CRCI for counties and Census tracts, data for each indicator, correlation analysis and top three drivers for the county CRCI. It also includes the NRI EAL data by Census tract and selected ClimRR layers.

RAPT Analysis Tools include the Population Counter, Incident Analysis Tool, Filter Tool, Add Data and the Grant Equity Threshold Tool (GETT). GETT supports Justice40 grant programs by providing population calculations for proposed benefitting areas. Within the benefitting area shape, GETT provides rapid determinations of the percentage of population living in a disadvantaged Census tract designated by the Climate and Economic Justice Screen Tool, the percentage of the population living in a Community Disaster Resilience Zone Census tract, and the percentage of the population living in each CRCI bin. Applicants can also download and submit a geospatial file with their grant application.

RAPT gives everyone the power of GIS analysis and allows users to combine and analyze the relationships among multiple data sets, locate critical infrastructure in high-risk areas, and determine population counts of people with specific attributes for drawn geographic areas. RAPT has been used for emergency operations planning, community outreach analysis, alerts and warning planning, evacuation operations, identifying cooling center locations, and transportation needs for at-risk populations.

FEMA National Risk Index (NRI)

The FEMA NRI assesses risk at a Census tract level for 18 natural hazards: Avalanche, Coastal Flooding, Cold Wave, Drought, Earthquake, Hail, Heatwave, Hurricane, Ice Storm, Landslide, Lightning, Riverine Flooding, Strong Wind, Tornado, Tsunami, Volcanic Activity, Wildfire, and Winter Weather. The NRI was designed and built starting in 2016 by FEMA in close collaboration with various stakeholders and partners in academia, local, state and federal government, and private industry. The NRI helps planners and emergency managers at the local, regional, state, and federal levels, as well as other decision makers and interested members of the general public, better understand the natural hazard risks to their communities.

The Risk Index leverages available source data for natural hazard and community risk factors to develop [a baseline risk measurement] for each U.S. county and Census tract. The NRI's interactive mapping and data-based interface enables users to visually explore individual datasets to better understand what is driving a community's natural hazard risk with minimal technical expertise. Users may also create reports to capture risk details on a community or conduct community-based risk comparisons, as well as export data for analysis using other software. A set of NRI best practices is available here: https://www.fema.gov/flood-maps/products-tools/national-risk-index/best-practices.

One example is through the Community Disaster Resilience Zones Act. In support of this Act, FEMA used the NRI and the Climate & Economic Justice Screening Tool to determine which Census tracts are most in need of assistance for resilience building projects and better coordinate across the public and private sectors to integrate investments and synergies in those identified zones.

FEMA is expanding the NRI by developing a prototype platform to project how climate change and future conditions will change impact of natural hazards in the mid- and late-century—a Climate Informed NRI. The natural hazards of focus are those that are most likely to increase impact due to climate change, have high current expected annualized losses, and for which there are suitable existing methodologies that can be used to estimate climate impacts. FEMA identified coastal flooding, drought, heatwave, hurricane wind, and wildfire for inclusion within a climate informed prototype under development, as of October 2023, and expected to be included in the NRI some time in calendar year 2024. All projects are based on current data exposure information.

The Climate Informed NRI approach is intended to be simplistic. It does not consider the impacts of adaptation or maladaptation in response to heightened levels of climate risk (e.g., population migration, mitigation measures, physiological acclimation to climate change). It also does not account for urbanization and development of suburban and rural areas. Such factors may drastically affect, increasing or reducing, actual future losses.

Developments in climate research have produced multiple sources of downscaled, high-resolution datasets describing projected future climate conditions. For Heatwave, Drought, and Wildfire downscaled CMIP5 data are being used. These data are available from two sources: Localized Constructed Analogs (LOCA and LOCA2) produced by the Scripps Institution of Oceanography, and the Climate Risk and Resilience Portal (ClimRR) produced by Argonne National Laboratory in collaboration with AT&T and FEMA. For Coastal Flooding, projected flood inundation layers and frequencies are produced by NOAA-Office for Coastal Management in the [2022 NOAA Technical Sea Level Rise Report]. For Hurricane (focus is on wind only), the data use information about the magnitude distribution of projected future hurricanes, produced by FEMA and Applied Research Associates.

The Climate Informed NRI projects climate change impact metrics by deriving Climate Informed Adjustment Factors from the data sources above. This factor is a multiplicative adjustment that is applied to the Expected Annual Loss (EAL), as calculated in the NRI. The calculation of the Climate Informed Adjustment Factor uses a climate variable that is highly correlated with an aspect of current losses. For example, Heatwave losses may be correlated with the number of days in a year where the nighttime temperature does not go below 80 degrees Fahrenheit. In this example, the climate metric ("Days in a year where the nighttime temperature does not go below 80 degrees") is compared against its projected value relative to today's value for each community in the NRI. If in a Climate Change scenario, the number of days exceeding this threshold is projected to be three times the current level, then the Climate Informed Adjustment Factor would be three for that community. The Climate Informed NRI's EAL value would be three times the NRI's EAL value. Finally, the platform will calculate the other projected metrics, such as index Scores and Ratings, relative to the present hazard levels and thresholds. Projections exclude decreases in hazard levels.

The methodology described captures the essence of the calculations that will be used in the Climate Informed NRI but omits some details. For example, FEMA completed the Coastal Flood hazard EAL calculations at a "sub hazard" level since NOAA provides its results separately for minor, moderate, and major coastal floods. Likewise, FEMA adapted the hurricane projections which were available at the Hurricane category "sub-hazard" level. In some cases, multiple variables were relevant for estimating climate change impacts. For example, for heatwave the following were considered:

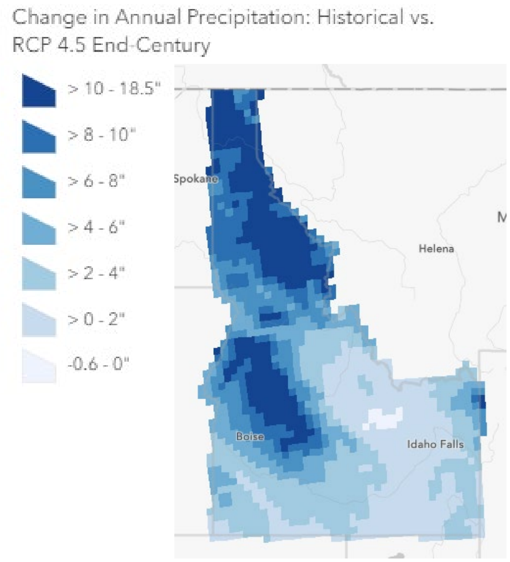
- Days with Nighttime Temperatures over 99th Percentile
- Days with Daytime Temperatures over 99th Percentile
- Days with Daytime Temperatures over 90 degrees
- Days with Nighttime Temperatures over 80 degrees

CASE STUDY – Idaho Hazard Mitigation Plan

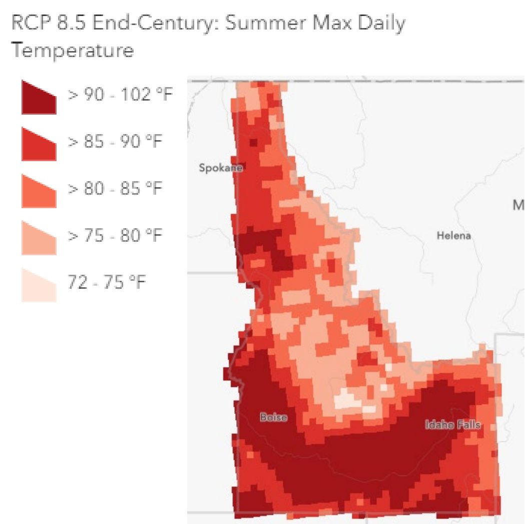
In Summer 2023, FEMA, AT&T, and the State of Idaho emergency management team worked together to incorporate ClimRR and RAPT data into their updated Hazard Mitigation Plan. The analysis included an ArcGIS StoryMap with extensive graphics and bar charts to convey the changing climate across the state. These visual displays offer immediate insights about coming climate challenges and anchor planning and mitigation strategies.

Key Findings: ClimRR Projections for Idaho

- Most of the state is projected to see increases in precipitation under both the more severe (RCP8.5) climate scenario and the less severe (RCP4.5) climate scenario that were analyzed. These precipitation increases are projected to occur primarily in the North, North Central, and Southwestern Regions of the state. reaching increases of 10 or more inches under RCP4.5 at end-of-century. And future precipitation will likely come as more intense, but less frequent events.
- Although annual precipitation is generally increasing for Idaho, the maximum consecutive days with no precipitation is also projected to increase for almost every county.



- Throughout the century, dangerous Fire Weather Index values are projected to spread eastward from Boise across the Snake River Plain, which could jeopardize crop yields and communities. The Fire Weather Index accounts for forecasted weather conditions that make fires more likely but does not account for vegetation or ignition scenarios.
- By the end of the century under the RCP8.5 climate scenario, 20 of Idaho's 44 counties are projected to experience average summer daily high temperatures of 90 degrees Fahrenheit or more, with Payette and Canyon reaching averages of 101 degrees Fahrenheit.



Case Study Lessons Learned

- Local data are key – Because state planning is conducted by state regions, breaking down the data by region was critical for the state.
- More isn't always better – Data must be selected carefully to highlight important findings.
- Review is essential – ClimRR and Idaho Emergency Management incorporated feedback from local stakeholders.
- Climate projections need to be linked to population impacts – hazards (and solutions) are more urgent when their human impacts are contextualized with demographic and infrastructure data. ClimRR is uniquely situated to provide this with FEMA's RAPT and associated FEMA CRCI data on resilience challenges.

CASE STUDY – Extreme Heat

RAPT can be used to prioritize locations for community cooling centers during extreme heat events by considering where concentrations of vulnerable populations are located. Vulnerable populations include populations over age 65, populations with a disability, and electricity-dependent Medicare individuals that rely on electrically powered devices. These individuals could face significant health challenges when heat waves cause loss of power, and RAPT allows Emergency Managers and city planners to identify where higher concentrations of these individuals reside. The RAPT also includes real-time weather watches and warnings from the National Weather Service, including Heat Advisory, Extreme Heat Watch, and Extreme Heat Warning information.

RAPT can be a powerful tool for city planners and Emergency Managers so that they can ensure an equitable and inclusive distribution of resources and support during these extreme heat events. Even users with no previous GIS knowledge can overlay multiple data layers at one time, which allows them to see the interplay of various community resilience factors and to apply these insights to disaster preparation, response, and recovery activities. Adding ClimRR data layers to RAPT allows users to see the projected climate information with today's population and infrastructure to plan for the future.

The Fifth National Climate Assessment Interactive Atlas and Climate Mapping for Resilience and Adaptation Updates

The AP chapter introduces the NCA5 Atlas and new updates to the Climate Mapping for Resilience and Adaptation (CMRA) portal. This section of the white paper expands on the discussion of those tools, and includes additional technical background on downscaling methods employed in the Fifth National Climate Assessment (NCA5).

The NCA5 Interactive Atlas provides digital access to downscaled projections of the physical climate data (temperature and precipitation) used in the NCA5. The Atlas will include projections of sea-level rise in the near future. The Atlas is an extension of NCA5, offering interactive maps that show projections of future conditions in the United States. While the NCA5 is a static report, the NCA5 Interactive Atlas allows users to access and explore NCA5 climate data for locations across the U.S., even if those data were not explicitly presented in figures within the NCA5 chapters.

The NCA Interactive Atlas also includes features to help users interpret and compare maps. These maps provide a plain-language summary and a swipe feature to compare projected conditions at various levels of global warming and precipitation.

Projections in the Atlas are from global climate models that participated in Phase 6 of the Coupled Model Intercomparison Project (CMIP6). To make the CMIP6 projections more decision-relevant at regional-to-local scales, results from global models were spatially downscaled using statistical methods documented by LOCA2 and STAR-ESDM. Further information can be found in NCA5 Appendix 3. Scenarios and Datasets.

With updated projections from the NCA5, the U.S. Climate Resilience Toolkit and Climate Mapping for Resilience and Adaptation (CMRA) portal will be updated and leveraged as primary knowledge-sharing hubs underpinning co-design and co-production of adaptation and resilience solutions, including by sharing real-world case studies on past and current resilience-building efforts. Using the NCA5 data as a foundation, the CMRA portal will be updated to represent the latest assessments of climate risks. For example, a new hazard topic – extreme cold – has already been added to the popular dashboard of real-time climate-related hazards. The user experience has been improved on CMRA including explaining that checking past and projected future climate is one of the first steps in protecting a community from climate hazards. CMRA reports will also better link to FEMA's National Risk Index and NOAA's Billion Dollar Disaster site will be included to provide additional context of climate risks.

Along with the NCA5 Interactive Atlas, these portals and tools represent implementation pilots of the Climate Resilience Information System (CRIS), which will provide the foundational information infrastructure needed for easy and consistent access to observed climatologies, climate projections, and other decision-relevant climate-related data. Collectively, these online resources represent a major opportunity to better support communities in localizing climate hazard data with other relevant information, such as infrastructure and socio-economic conditions.

Following the NCA5 release with accessible and updated climate projections, and updated tools and portals, there are opportunities to operationalize the Federal Framework and Action Plan for Climate Services to develop a federal data policy governing design and development of climate services, especially for managing climate risk exposure.

This action would develop whole-of-government guidance regarding the development and use of climate data and products intended for public use in planning and decision making. This policy should a) be consistent with the Federal Data Strategy and the Information Quality Act; b) promote the use of open data standards; and c) integrate guidance on the use of Indigenous Knowledge in the development and use of climate services. The policy would span multiple considerations, including the following:

- Definitions of consistent application of metadata standards, appropriate data formats, practices for maintaining data interoperability and analysis ready data for climate-risk related artificial intelligence and machine learning applications, and the crediting of data sources and providers.
- Processes for the application of open data standards and the conditions under which data are, or are not, made publicly available and the mechanisms for doing so.
- Methods for the consistent application of scenarios, model ensembles, and uncertainty characterization in the development and delivery of climate services.
- Mechanisms for maintaining climate data, product, and tool quality assurance to ensure services are scientifically credible and sanctioned for use by the Federal Government.
- Best practices for ensuring equity and inclusion in data acquisition and use, including processes for providing services to disadvantaged and minority communities, and for enhancing the appropriate use of Indigenous traditional and local knowledge in the development, and delivery of climate services.

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Appendix A: Modeling the financial climate risk of the Livestock Forage Disaster Program

To model the impact of drought on LFP payments, the report leverages a panel data econometric model to estimate how an additional month of eligibility for LFP translates into increased program expenditure. Specifically, the following model is estimated.

$$\begin{aligned} Y_{i,t} = \beta_1 LPF\ Months_{i,t} &+ \beta_2 Beef\ Cattle_{i,t} \\ &+ \beta_3(LPF\ Months_{i,t}\ X\ Beef\ Cattle_{i,t}) + \beta_4 Dairy\ Cattle_{i,t} \\ &+ \beta_5(LPF\ Months_{i,t}\ X\ Dairy\ Cattle_{i,t}) + \beta_6 Sheep_{i,2017} \\ &+ \beta_7(LPF\ Months_{i,t}\ X\ Sheep_{i,2017}) + \beta_8 Goats_{i,t} \\ &+ \beta_9(LPF\ Months_{i,t}\ X\ Goats_{i,2017}) + \beta_{10} Equine_{i,2017} \\ &+ \beta_{11}(LPF\ Months_{i,t}\ X\ Equine_{i,2017}) + \delta_t + \varepsilon_{i,t} \end{aligned} \qquad \text{A.1}$$

Where $Y_{i,t}$ represents the total LFP payments made to livestock producers in county *i* in time *t*. $Y_{i,t}$ is modeled as a function of the number of months of LFP payments livestock producers in county *i* were eligible to receive in time *t* ($LPF\ Months_{i,t}$), and separate variables accounting for the number of beef cattle, dairy cattle, sheep, goats, and equine species (i.e., donkey, burros, horses, mules, and ponies) in county *i* during time *t* as well as interactions between each of these livestock herd size variables and $LPF\ Months_{i,t}$, a year fixed effect (δ_t), and an idiosyncratic error term ($\varepsilon_{i,t}$). The estimated parameter β_1 represents the marginal impact of an additional month of LFP payments on total county-level payments conditional on the number of cattle within county *i*. Similarly, the parameters $\beta_2, \beta_4, \beta_6, \beta_8$ and β_{10} represents the marginal impact of additional head of livestock on total county-level LFP payments, conditional on the number of months of LFP payments producers in county *i* were eligible to receive. Finally, the parameters $\beta_3, \beta_5, \beta_7, \beta_9$ and β_{11} depicts how the relationship between months of eligible and total payments differs as a function of the number of differing types of livestock in county *i*. Including this interaction term is important as LFP payments are made on a per-head of livestock basis i.e., the relationship between months of LFP payments and total payments depends on the number of livestock within county *i*. The parameters $\beta_3, \beta_5, \beta_7, \beta_9$ and β_{11} capture this relationship by accounting for the impact of a higher county-level herd size on the marginal impact of an additional month of LFP eligibility. δ_t accounts for any common shocks within a given year (i.e., market conditions, cattle cycle, etc.).

The model outlined in equation A.1 is estimated using data collected from a variety of public and administrative sources. The outcome variable, county-level annual LFP payments between 2014 and 2022, were obtained from USDA-FSA based on their administrative records. Months of LFP eligibility were calculated by joining LFP eligible grazing periods to drought severity data reported by the U.S. Drought Monitor for the 2014 to 2022 time periods. Finally, species specific livestock herd size variables for sheep, goats, and equine species come from USDA-NASS' 2017 Census of Agriculture and are time invariant in the model. Beef and dairy cattle herd size are time variant and drawn from USDA-NASS's Cattle Survey. Results of the model outlined in equation A.1 are presented in table A.1.

Table A.1 Modeling results: Relationship between LFP payments and drought

	Dependent variable:
	LFP payments (2022 dollars)
LFP Months (months of eligibility)	207,099.200***
	(10,206.270)
Beef cattle (count)	1.596***
	(0.191)
Beef cattle X LFP Months	11.753***
	(0.775)
Dairy cattle (count)	0.127
	(0.185)
Dairy cattle X LFP Months	-1.069***
	(0.296)
Sheep (count)	0.823
	(0.746)
Sheep X LFP Months	1.429**
	(0.702)
Goats (count)	1.368
	(1.263)
Goats X LFP Months	-0.169
	(1.377)
Equine (count)	43.793***
	(11.439)
Equine X LFP Months	-35.040*
	(18.007)
Observations	28,065
R^2	0.469
Adjusted R^2	0.469
Residual Std. Error	576,532.900 (df = 28045)
Note:	*p**p***p<0.01

Source: USDA, Economic Research Service using data from USDA-NASS and USDA-FSA.

The parameters estimated by the panel data model are used to predict county-level LFP payments under differing projections of drought conditions which influence the number of months of LFP payments livestock producers are eligible to receive. Specifically, for the i^{th} county in future time period t, predicted LFP payments, $\hat{Y}_{i,t}$, are as follows:

$$\begin{aligned}\hat{Y}_{i,t} = {} & \hat{\beta}_1 LFP\ Months(Climate\ Scenario_{i,j,t}) + \hat{\beta}_2 Beef\ Cattle_{i,2022} \\ & + \hat{\beta}_3(LFP\ Months(Climate\ Scenario_{i,j,t})\ X\ Beef\ Cattle_{i,2022}) \\ & + \hat{\beta}_4\ Dairy\ Cattle_{i,2022} \\ & + \hat{\beta}_5(LFP\ Months(Climate\ Scenario_{i,j,t})\ X\ Dairy\ Cattle_{i,2022}) \\ & + \hat{\beta}_6\ Sheep_{i,2017} \\ & + \hat{\beta}_7(LFP\ Months(Climate\ Scenario_{i,j,t})\ X\ Sheep_{i,2017}) \\ & + \hat{\beta}_8\ Goats_{i,2017} \\ & + \hat{\beta}_9(LFP\ Months(Climate\ Scenario_{i,j,t})\ X\ Goats_{i,2017}) \\ & + \hat{\beta}_{10}\ Equine_{i,2017} \\ & + \hat{\beta}_{11}(LFP\ Months(Climate\ Scenario_{i,j,t})\ X\ Equine_{i,2017}) +\end{aligned} \quad \text{A.2}$$

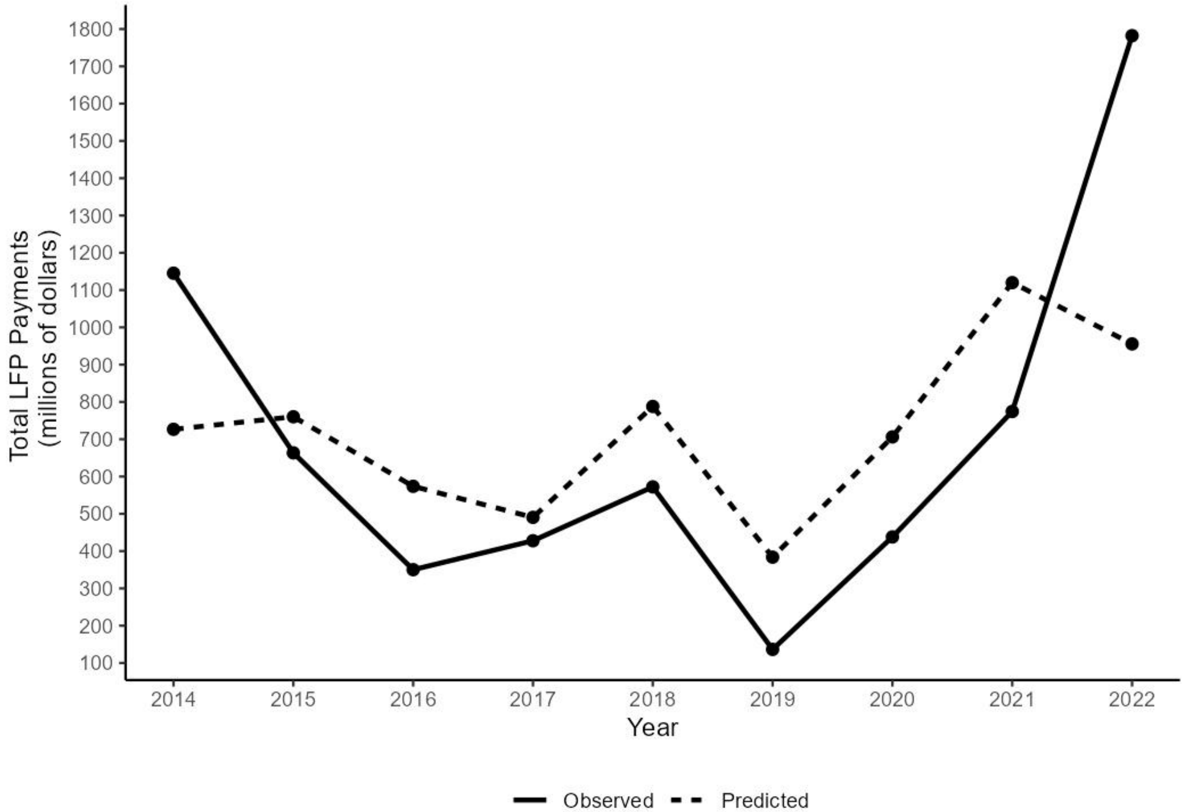
$LFP\ Months(Climate\ Scenario_{i,j,t})$ is a function relating the j^{th} climate scenario to the i^{th} county's months of LFP eligibility in future time period *t.* The prediction model uses these estimates of future months of LFP eligibility as well as the parameters estimated by equation B.1 to simulate county-level payments recognizing the important relationship between the quantity of livestock within a given county and the marginal impact of an additional month of LFP eligibility on total LFP county-level payments. The time effect, δ_t, is set to zero in the prediction model which implicitly assumes that the common shocks experienced between 2014 and 2022 reflect common shocks in the future. This is a strong assumption given the likelihood that common shocks influencing the relationship between months of LFP eligibility and cattle herd size on LFP payments (e.g., market conditions, regulations, LFP policy changes, etc.) may change in the future. However, modeling these changes which depend on political, economic, and climatic factors is outside of the scope of this report. Instead, this analysis assumes that the attributes of the LFP (e.g., eligibility criteria) remain constant in the future.

To predict future county-level LFP payments, this report uses months of LFP eligibility projected by an ensemble of climate projection models across differing emissions scenarios (see "Emissions Scenarios" text box). These projected months of eligibility are then joined with the most recent county-level species-specific data on livestock herd size to predict LFP payments. For beef and dairy cattle, these data are from USDA-NASS' 2022 Cattle Survey. For sheep, goats, and equine species these data are from USDA-NASSs 2017 Census of Agriculture. This methodology implicitly assumes that county-level livestock herd sizes will not respond to climatic factors. For example, persistent future drought conditions in a given region may induce adaptation among livestock producers through reductions in their herd size. This model does not account for these adaptations. How the livestock sector will adapt to evolving climate conditions is an important avenue for future research efforts, however, modeling that adaptation lies outside of the scope of this report.

To assess the accuracy of the panel fixed effects model estimates in predicting LFP payments this report compares observed aggregate LFP payments between 2014 and 2022 to predicted payments estimated using the simulation model. Specifically, equation B.2 is used to predict county-level LFP payments between 2014 and 2022. Estimated county-level LFP payments are aggregated annually and plotted in figure B.1 along with the observed annual aggregate payments.

Figure A.1 demonstrates that over the 2014 to 2022 time period, the LFP payment prediction model does not consistently overestimate or underestimate aggregate LFP payments. Predicted LFP payments generally follow the LFP payment trends which correlate with drought severity in livestock production areas.

Figure A.1. Observed and Predicted Annual Aggregate LFP Payments, 2014-2022



Note: This figure plots observed and predicted annual aggregate LPF payments between 2014 and 2022. Predicted annual aggregate LFP payments are generated using output from a panel data model estimating the relationship between annual county-level LFP payments and the number of months of LFP payments livestock producers in each county are eligible to receive, the counts of livestock within the county by type (beef/dairy cattle, sheep, goats, and equine species – horses, ponies, mules, donkeys, and burros), and an interaction between livestock count variables and months of payments. When predicting LFP payments between 2014 and 2022, the estimated time effect, δ_t, is not incorporated.

Source: USDA, Economic Research Service using data provided by USDA, Farm Service Agency and parameter estimates generated by econometric modeling code provided by R package LFE.

Appendix B: Livestock Forage Disaster Program Assessment - Projections of Future Drought Conditions

To predict future drought conditions under differing emissions scenarios and drought classification methods, the LFP assessment leverages output from a suite of climate projection models to predict future USDM drought classifications through 2100 for a range of emissions scenarios. The process described below is conducted for each of the climate scenarios considered in this report.

The process of predicting future drought conditions begins with calculating daily reference evapotranspiration (ETr) for grass (i.e., forage) using the Penman Monteith method (Zotarelli et al., 2010). Estimated ETr is then joined to output from the suite of climate models on daily precipitation through 2100 to calculate water balance as precipitation (P) less ETr i.e., water balance = P – ETr. These daily observations of water balance are then aggregated over 30, 60, and 90 day timescales and the Generalized Logistic (GLO) distribution parameters for these aggregations are estimated over the period of record (POR) which incorporate climatic data from 1951 onward and 30-year running climatologies using L-moments (Hosking, 1990; Vicente-Serrano et al., 2010).

Water balance aggregations and their estimated distribution parameters are translated into Standardized Precipitation-Evapotranspiration Index (SPEI) by projecting quantiles into a normalized distribution i.e., normalizing each distribution. SPEI is then downscaled to short-term blends by averaging across 30-, 60-, and 90-day timescales. The short-term SPEI values are classified into USDM probabilistic classifications using thresholds reported by USDM associating given drought classifications with values of SPEI. Specifically, this report uses the following SPEI ranges and probability classifications to translate SPEI to USDM categories.

- D4: <= 2% (equivalent to SPEI <= -2.054)
- D3: >2% and <= 5% (SPEI > -2.054 and <= -1.645)
- D2: >5% and <= 10% (SPEI > -1.645 and <= -1.282)
- D1: >10% and <= 20% (SPEI > -1.282 and <= -0.842)
- D0: >20% and <= 30% (SPEI > -0.842 and <= -0.524)

These estimated USDM classifications are then aggregated at the county level, taking the highest (most severe) drought class per county as LFP eligibility is a function of the most severe drought conditions in a given county. Finally, these USDM classifications are translated into months of county-level LFP eligibility by year for each eligible grazing period and the maximum number of months of LFP payments across all eligible grazing periods is applied to each county-year prediction.

Appendix C: Burned Area Models for the Department of the Interior and USDA Forest Service

Table C.1. Department of the Interior Area Burned Poisson Pseudo-Maximum Likelihood Equation Estimates, Monthly Data, January 1998 to December 2019.

Bureau	Region	Variable	Parameter Estimate	Standard Error	t-value	p-value	Obser-vations
BIA	1	Ln(VPD_t)	12.63	1.31	9.65	0.00	264
		Ln(Max T °K_t)	-214.15	25.99	-8.24	0.00	
		Constant	1225.64	147.80	8.29	0.00	
BIA	2	Ln(VPD_t)	6.68	2.23	3.00	0.00	264
		Ln(Max T °K_t)	-89.98	47.03	-1.91	0.06	
		Constant	519.29	267.20	1.94	0.05	
BIA	3	Ln(VPD_t)	12.88	3.66	3.52	0.00	264
		Ln(Max T °K_t)	-167.79	51.24	-3.27	0.00	
		Constant	957.61	290.28	3.30	0.00	
BIA	4	Ln(VPD_t)	1.19	7.08	0.17	0.87	264
		Ln(Max T °K_t)	86.66	127.42	0.68	0.50	
		Constant	-487.22	722.63	-0.67	0.50	
BIA	5	Ln(VPD_t)	-4.56	1.85	-2.46	0.01	264
		Ln(Max T °K_t)	128.68	53.97	2.38	0.02	
		Constant	-726.12	307.08	-2.36	0.02	
BIA	6	Ln(VPD_t)	4.87	3.96	1.23	0.22	264
		Ln(Max T °K_t)	-24.63	84.07	-0.29	0.77	
		Constant	148.15	478.10	0.31	0.76	
BIA	8	Ln(VPD_t)	7.04	0.96	7.34	0.00	264
		Ln(Max T °K_t)	-134.79	18.33	-7.35	0.00	
		Constant	777.09	104.40	7.44	0.00	

Bureau	Region	Variable	Parameter Estimate	Standard Error	t-value	p-value	Obser-vations
BIA	9	$Ln(VPD_t)$	12.20	2.52	4.85	0.00	264
		$Ln(Max\ T\ ^oK_t)$	-231.86	48.23	-4.81	0.00	
		Constant	1327.42	274.60	4.83	0.00	
BLM	1	$Ln(VPD_t)$	13.79	3.09	4.47	0.00	264
		$Ln(Max\ T\ ^oK_t)$	-191.44	58.75	-3.26	0.00	
		Constant	1096.19	333.80	3.28	0.00	
BLM	2	$Ln(VPD_t)$	7.12	2.68	2.65	0.01	264
		$Ln(Max\ T\ ^oK_t)$	-79.09	52.85	-1.50	0.14	
		Constant	457.23	300.10	1.52	0.13	
BLM [a]	2	$Ln(VPD_t)$	3.17	0.45	6.99	0.00	264
		$Ln(Max\ T\ ^oK_t)$					
		Constant	8.09	0.23	35.52	0.00	
BLM	3	$Ln(VPD_t)$	10.56	1.83	5.76	0.00	264
		$Ln(Max\ T\ ^oK_t)$	-165.52	36.39	-4.55	0.00	
		Constant	946.53	206.53	4.58	0.00	
BLM	4	$Ln(VPD_t)$	-4.04	3.17	-1.27	0.20	264
		$Ln(Max\ T\ ^oK_t)$	167.92	64.65	2.60	0.01	
		Constant	-944.17	367.04	-2.57	0.01	
BLM [a]	4	$Ln(VPD_t)$	4.27	0.78	5.43	0.00	264
		$Ln(Max\ T\ ^oK_t)$					
		Constant	9.03	0.63	14.26	0.00	
BLM	5	$Ln(VPD_t)$	1.32	4.90	0.27	0.79	264
		$Ln(Max\ T\ ^oK_t)$	23.45	105.67	0.22	0.82	
		Constant	-125.83	599.92	-0.21	0.83	
BLM [a]	5	$Ln(VPD_t)$	2.50	0.62	4.04	0.00	264

Bureau	Region	Variable	Parameter Estimate	Standard Error	t-value	p-value	Obser-vations
		Ln(Max T °K_t)					
		Constant	7.19	0.67	10.79	0.00	
BLM	6	Ln(VPD_t)	-0.98	3.38	-0.29	0.77	264
		Ln(Max T °K_t)	136.64	78.39	1.74	0.08	
		Constant	-768.42	445.66	-1.72	0.09	
BLM [a]	6	Ln(VPD_t)	5.18	0.81	6.39	0.00	264
		Ln(Max T °K_t)					
		Constant	8.21	0.41	20.18	0.00	
BLM	8	Ln(VPD_t)	ND	ND	ND	ND	264
		Ln(Max T °K_t)	ND	ND	ND	ND	
		Constant	ND	ND	ND	ND	
BLM	9	Ln(VPD_t)	ND	ND	ND	ND	264
		Ln(Max T °K_t)	ND	ND	ND	ND	
		Constant	ND	ND	ND	ND	
FWS	1	Ln(VPD_t)	6.40	1.80	3.56	0.00	264
		Ln(Max T °K_t)	-92.82	36.64	-2.53	0.01	
		Constant	535.21	208.37	2.57	0.01	
FWS	2	Ln(VPD_t)	4.72	1.35	3.50	0.00	264
		Ln(Max T °K_t)	-83.85	26.33	-3.18	0.00	
		Constant	484.34	149.93	3.23	0.00	
FWS	3	Ln(VPD_t)	3.32	3.98	0.83	0.40	264
		Ln(Max T °K_t)	-29.61	64.48	-0.46	0.65	
		Constant	173.21	365.09	0.47	0.64	
FWS	4	Ln(VPD_t)	-5.73	6.77	-0.85	0.40	264

Bureau	Region	Variable	Parameter Estimate	Standard Error	t-value	p-value	Obser-vations
		Ln(Max T °K_t)	167.28	158.42	1.06	0.29	
		Constant	-944.35	899.92	-1.05	0.29	
FWS	5	Ln(VPD_t)	2.94	2.44	1.20	0.23	264
		Ln(Max T °K_t)	-65.31	72.13	-0.91	0.37	
		Constant	378.12	411.22	0.92	0.36	
FWS	6	Ln(VPD_t)	4.98	4.89	1.02	0.31	264
		Ln(Max T °K_t)	-53.18	118.98	-0.45	0.66	
		Constant	310.41	676.61	0.46	0.65	
FWS	8	Ln(VPD_t)	8.07	2.43	3.33	0.00	264
		Ln(Max T °K_t)	-112.03	38.24	-2.93	0.00	
		Constant	648.07	218.12	2.97	0.00	
FWS	9	Ln(VPD_t)	3.19	1.31	2.44	0.02	264
		Ln(Max T °K_t)	-63.57	29.29	-2.17	0.03	
		Constant	368.76	166.59	2.21	0.03	
NPS	1	Ln(VPD_t)	6.92	2.87	2.41	0.02	264
		Ln(Max T °K_t)	-50.91	60.96	-0.84	0.40	
		Constant	297.30	346.42	0.86	0.39	
NPS	2	Ln(VPD_t)	8.60	3.64	2.36	0.02	264
		Ln(Max T °K_t)	-168.75	93.31	-1.81	0.07	
		Constant	964.84	529.69	1.82	0.07	
NPS	3	Ln(VPD_t)	11.91	3.16	3.77	0.00	264
		Ln(Max T °K_t)	-184.15	59.33	-3.10	0.00	
		Constant	1049.69	336.60	3.12	0.00	
NPS	4	Ln(VPD_t)	-2.16	4.39	-0.49	0.62	264
		Ln(Max T °K_t)	124.40	76.81	1.62	0.11	

Bureau	Region	Variable	Parameter Estimate	Standard Error	t-value	p-value	Obser-vations
		Constant	-702.53	435.32	-1.61	0.11	
NPS	5	Ln(VPD_t)	1.69	4.31	0.39	0.69	264
		Ln(Max T ^oK_t)	1.91	103.90	0.02	0.99	
		Constant	-4.10	589.79	-0.01	0.99	
NPS	6	Ln(VPD_t)	1.15	2.66	0.43	0.67	264
		Ln(Max T ^oK_t)	113.64	69.19	1.64	0.10	
		Constant	-638.19	393.74	-1.62	0.11	
NPS	8	Ln(VPD_t)	11.34	2.33	4.87	0.00	264
		Ln(Max T ^oK_t)	-166.47	48.12	-3.46	0.00	
		Constant	957.10	274.29	3.49	0.00	
NPS	9	Ln(VPD_t)	4.89	1.22	4.02	0.00	264
		Ln(Max T ^oK_t)	-83.69	23.33	-3.59	0.00	
		Constant	481.72	132.83	3.63	0.00	

[a] Parsimonious specification used in modeling.

Table C.2. Department of the Interior Regressions of the Sum of the Square Root of Area Burned for All Fires Poisson Pseudo-Maximum Likelihood Equation Estimates, Monthly Data, January 1998 to December 2019.

Bureau	Region	Variable	Parameter Estimate	Standard Error	t-value	p-value	Observations
BIA	1	Ln(VPD_t)	6.54	0.55	11.82	0.00	264
		Ln(Max T ^oK_t)	-116.11	11.79	-9.85	0.00	
		Constant	665.56	67.05	9.93	0.00	
BIA	2	Ln(VPD_t)	4.85	0.61	7.97	0.00	264
		Ln(Max T ^oK_t)	-76.64	11.44	-6.70	0.00	

Bureau	Region	Variable	Parameter Estimate	Standard Error	t-value	p-value	Observations
		Constant	440.54	65.02	6.78	0.00	
BIA	3	$Ln(VPD_t)$	4.93	0.50	9.95	0.00	264
		$Ln(Max\ T\ {}^oK_t)$	-63.97	9.70	-6.60	0.00	
		Constant	367.10	55.03	6.67	0.00	
BIA	4	$Ln(VPD_t)$	2.18	1.72	1.27	0.20	264
		$Ln(Max\ T\ {}^oK_t)$	3.62	37.41	0.10	0.92	
		Constant	-18.23	212.28	-0.09	0.93	
BIA	5	$Ln(VPD_t)$	-0.72	0.90	-0.80	0.42	264
		$Ln(Max\ T\ {}^oK_t)$	58.16	17.97	3.24	0.00	
		Constant	-328.30	102.01	-3.22	0.00	
BIA	6	$Ln(VPD_t)$	1.62	0.60	2.68	0.01	264
		$Ln(Max\ T\ {}^oK_t)$	10.45	15.54	0.67	0.50	
		Constant	-54.81	88.39	-0.62	0.54	
BIA	8	$Ln(VPD_t)$	6.73	0.48	14.01	0.00	264
		$Ln(Max\ T\ {}^oK_t)$	-131.93	9.15	-14.41	0.00	
		Constant	757.39	52.17	14.52	0.00	
BIA	9	$Ln(VPD_t)$	9.13	0.52	17.72	0.00	264
		$Ln(Max\ T\ {}^oK_t)$	-167.53	9.56	-17.53	0.00	
		Constant	959.02	54.44	17.62	0.00	
BLM	1	$Ln(VPD_t)$	7.61	1.29	5.89	0.00	264
		$Ln(Max\ T\ {}^oK_t)$	-96.45	26.45	-3.65	0.00	
		Constant	552.75	150.35	3.68	0.00	
BLM	2	$Ln(VPD_t)$	3.35	0.90	3.71	0.00	264
		$Ln(Max\ T\ {}^oK_t)$	-11.85	18.49	-0.64	0.52	
		Constant	71.86	105.00	0.68	0.49	

Bureau	Region	Variable	Parameter Estimate	Standard Error	t-value	p-value	Observations
BLM	2 [a]	Ln(VPD_t)	2.76	0.16	17.23	0.00	264
		Ln(Max T ^oK_t)					
		Constant	4.55	0.07	61.68	0.00	
BLM	3	Ln(VPD_t)	5.90	0.89	6.67	0.00	264
		Ln(Max T ^oK_t)	-77.79	17.39	-4.47	0.00	
		Constant	444.99	98.72	4.51	0.00	
BLM	4	Ln(VPD_t)	-1.78	1.72	-1.03	0.30	264
		Ln(Max T ^oK_t)	105.05	35.13	2.99	0.00	
		Constant	-591.23	199.40	-2.97	0.00	
BLM	4 [a]	Ln(VPD_t)	3.38	0.26	13.12	0.00	264
		Ln(Max T ^oK_t)					
		Constant	5.12	0.20	25.96	0.00	
BLM	5	Ln(VPD_t)	0.73	1.32	0.55	0.58	264
		Ln(Max T ^oK_t)	29.09	27.77	1.05	0.30	
		Constant	-161.67	157.64	-1.03	0.31	
BLM	5 [a]	Ln(VPD_t)	2.19	0.14	15.49	0.00	264
		Ln(Max T ^oK_t)					
		Constant	3.35	0.14	23.59	0.00	
BLM	6	Ln(VPD_t)	-0.52	1.04	-0.50	0.62	264
		Ln(Max T ^oK_t)	88.42	25.34	3.49	0.00	
		Constant	-497.98	144.06	-3.46	0.00	
BLM	6 [a]	Ln(VPD_t)	3.32	0.26	12.58	0.00	264
		Ln(Max T ^oK_t)					
		Constant	4.66	0.11	42.37	0.00	
BLM	8	Ln(VPD_t)	ND	ND	ND	ND	264

Bureau	Region	Variable	Parameter Estimate	Standard Error	t-value	p-value	Observations
		Ln(Max T °K_t)	ND	ND	ND	ND	
		Constant	ND	ND	ND	ND	
BLM	9	Ln(VPD_t)	ND	ND	ND	ND	264
		Ln(Max T °K_t)	ND	ND	ND	ND	
		Constant	ND	ND	ND	ND	
FWS	1	Ln(VPD_t)	5.83	0.92	6.34	0.00	264
		Ln(Max T °K_t)	-98.68	18.73	-5.27	0.00	
		Constant	565.00	106.52	5.30	0.00	
FWS	2	Ln(VPD_t)	4.76	0.82	5.81	0.00	264
		Ln(Max T °K_t)	-84.04	14.91	-5.63	0.00	
		Constant	481.79	84.90	5.67	0.00	
FWS	3	Ln(VPD_t)	4.78	1.66	2.88	0.00	264
		Ln(Max T °K_t)	-62.56	29.45	-2.12	0.03	
		Constant	356.39	166.90	2.14	0.03	
FWS	4	Ln(VPD_t)	-1.38	3.15	-0.44	0.66	264
		Ln(Max T °K_t)	71.82	70.85	1.01	0.31	
		Constant	-406.31	402.40	-1.01	0.31	
FWS	5	Ln(VPD_t)	-0.05	0.69	-0.08	0.94	264
		Ln(Max T °K_t)	29.68	20.17	1.47	0.14	
		Constant	-166.28	114.94	-1.45	0.15	
FWS	6	Ln(VPD_t)	1.92	1.88	1.02	0.31	264
		Ln(Max T °K_t)	10.70	46.75	0.23	0.82	
		Constant	-57.41	265.89	-0.22	0.83	
FWS	8	Ln(VPD_t)	3.97	0.50	7.88	0.00	264
		Ln(Max T °K_t)	-52.65	8.50	-6.20	0.00	

Bureau	Region	Variable	Parameter Estimate	Standard Error	t-value	p-value	Observations
		Constant	305.51	48.46	6.30	0.00	
FWS	9	$Ln(VPD_t)$	4.36	0.57	7.65	0.00	264
		$Ln(Max\ T\ {}^oK_t)$	-89.29	11.20	-7.98	0.00	
		Constant	512.22	63.76	8.03	0.00	
NPS	1	$Ln(VPD_t)$	5.11	2.41	2.12	0.03	264
		$Ln(Max\ T\ {}^oK_t)$	-32.16	50.33	-0.64	0.52	
		Constant	186.47	286.00	0.65	0.51	
NPS	2	$Ln(VPD_t)$	5.01	1.39	3.61	0.00	264
		$Ln(Max\ T\ {}^oK_t)$	-73.77	32.87	-2.24	0.03	
		Constant	421.70	186.77	2.26	0.02	
NPS	3	$Ln(VPD_t)$	4.98	1.92	2.59	0.01	264
		$Ln(Max\ T\ {}^oK_t)$	-35.12	38.59	-0.91	0.36	
		Constant	199.56	219.07	0.91	0.36	
NPS	4	$Ln(VPD_t)$	-3.23	1.58	-2.05	0.04	264
		$Ln(Max\ T\ {}^oK_t)$	120.60	34.53	3.49	0.00	
		Constant	-683.25	195.88	-3.49	0.00	
NPS	5	$Ln(VPD_t)$	-1.78	1.69	-1.05	0.29	264
		$Ln(Max\ T\ {}^oK_t)$	82.51	39.86	2.07	0.04	
		Constant	-465.79	226.27	-2.06	0.04	
NPS	6	$Ln(VPD_t)$	0.77	1.35	0.58	0.57	264
		$Ln(Max\ T\ {}^oK_t)$	84.74	33.79	2.51	0.01	
		Constant	-477.73	192.31	-2.48	0.01	
NPS	8	$Ln(VPD_t)$	5.49	0.55	10.00	0.00	264
		$Ln(Max\ T\ {}^oK_t)$	-70.92	9.26	-7.66	0.00	
		Constant	408.75	52.80	7.74	0.00	

Bureau	Region	Variable	Parameter Estimate	Standard Error	t-value	p-value	Observations
NPS	9	Ln(VPD_t)	4.86	0.45	10.91	0.00	264
		Ln(Max T ^oK_t)	-81.05	7.82	-10.37	0.00	
		Constant	464.76	44.54	10.43	0.00	

[a] Parsimonious specification used in modeling.

Table C.3. USDA Forest Service National Forest Area Burned Poisson Pseudo-Maximum Likelihood Equation Estimates, Monthly Data, January 1998 to December 2019. (Note: National Forest indicator variable parameter estimates withheld to limit table size; these are available upon request.)

Region	Variable	Parameter Estimate	Standard Error	t-value	p-value	Observations
1	Ln(VPD_t)	10.52	1.76	5.97	0.00	2640
	Ln(Max T ^oK_t)	-106.63	42.29	-2.52	0.01	
	Ln(Sum of Area Burned t-13 to t-24)	0.04	0.04	1.05	0.30	
	Ln(Sum of Area Burned t-25 to t-36)	-0.09	0.05	-1.86	0.06	
	Ln(Sum of Area Burned t-37 to t-48)	0.13	0.05	2.45	0.01	
	Ln(Sum of Area Burned t-49 to t-60)	-0.03	0.04	-0.57	0.57	
2	Ln(VPD_t)	11.38	1.54	7.40	0.00	2640
	Ln(Max T ^oK_t)	-144.88	28.85	-5.02	0.00	
	Ln(Sum of Area Burned t-13 to t-24)	0.03	0.05	0.56	0.57	
	Ln(Sum of Area Burned t-25 to t-36)	-0.02	0.05	-0.46	0.64	
	Ln(Sum of Area Burned t-37 to t-48)	-0.09	0.05	-1.77	0.08	
	Ln(Sum of Area Burned t-49 to t-60)	-0.03	0.05	-0.67	0.51	
3	Ln(VPD_t)	8.46	1.06	8.00	0.00	2640
	Ln(Max T ^oK_t)	-119.45	27.27	-4.38	0.00	
	Ln(Sum of Area Burned t-13 to t-24)	0.15	0.06	2.48	0.01	

	Ln(Sum of Area Burned t-25 to t-36)	-0.11	0.06	-1.75	0.08	
	Ln(Sum of Area Burned t-37 to t-48)	0.01	0.08	0.18	0.86	
	Ln(Sum of Area Burned t-49 to t-60)	0.00	0.05	-0.01	0.99	
4	Ln(VPD_t)	9.99	1.68	5.94	0.00	2640
	Ln(Max T ^oK_t)	-81.96	37.89	-2.16	0.03	
	Ln(Sum of Area Burned t-13 to t-24)	-0.01	0.04	-0.27	0.79	
	Ln(Sum of Area Burned t-25 to t-36)	-0.21	0.07	-3.02	0.00	
	Ln(Sum of Area Burned t-37 to t-48)	0.07	0.06	1.27	0.20	
	Ln(Sum of Area Burned t-49 to t-60)	-0.08	0.05	-1.48	0.14	
5	Ln(VPD_t)	9.11	1.91	4.77	0.00	2640
	Ln(Max T ^oK_t)	-117.85	39.48	-2.99	0.00	
	Ln(Sum of Area Burned t-13 to t-24)	0.00	0.06	0.08	0.94	
	Ln(Sum of Area Burned t-25 to t-36)	-0.05	0.04	-1.45	0.15	
	Ln(Sum of Area Burned t-37 to t-48)	-0.07	0.06	-1.22	0.22	
	Ln(Sum of Area Burned t-49 to t-60)	-0.04	0.04	-0.88	0.38	
6	Ln(VPD_t)	4.29	1.86	2.30	0.02	2640
	Ln(Max T ^oK_t)	62.15	51.18	1.21	0.23	

	Ln(Sum of Area Burned t-13 to t-24)	-0.08	0.07	-1.18	0.24	
	Ln(Sum of Area Burned t-25 to t-36)	-0.01	0.05	-0.24	0.81	
	Ln(Sum of Area Burned t-37 to t-48)	-0.03	0.05	-0.68	0.50	
	Ln(Sum of Area Burned t-49 to t-60)	-0.13	0.08	-1.56	0.12	
8	Ln(VPD_t)	8.00	0.87	9.24	0.00	2640
	Ln(Max T ^oK_t)	-120.09	13.35	-9.00	0.00	
	Ln(Sum of Area Burned t-13 to t-24)	-0.16	0.08	-1.95	0.05	
	Ln(Sum of Area Burned t-25 to t-36)	-0.13	0.04	-3.03	0.00	
	Ln(Sum of Area Burned t-37 to t-48)	0.00	0.11	0.04	0.97	
	Ln(Sum of Area Burned t-49 to t-60)	-0.04	0.11	-0.31	0.76	
9	Ln(VPD_t)	6.51	0.71	9.20	0.00	2640
	Ln(Max T ^oK_t)	-89.94	12.56	-7.16	0.00	
	Ln(Sum of Area Burned t-13 to t-24)	-0.04	0.11	-0.34	0.74	
	Ln(Sum of Area Burned t-25 to t-36)	-0.19	0.12	-1.55	0.12	
	Ln(Sum of Area Burned t-37 to t-48)	-0.41	0.07	-5.49	0.00	
	Ln(Sum of Area Burned t-49 to t-60)	0.17	0.11	1.65	0.10	
1 [a]	Ln(VPD_t)	9.96	1.78	5.60	0.00	2640

	Ln(Max T $^{o}K_t$)	-88.46	44.50	-1.99	0.05	
	Sum of Ln(Sum of Area Burned t-13 to t-24) to Ln(Sum of Area Burned t-49 to t-60)	-0.01	0.03	-0.22	0.83	
2 [a]	Ln(VPD_t)	11.41	1.56	7.32	0.00	2640
	Ln(Max T $^{o}K_t$)	-144.96	29.01	-5.00	0.00	
	Sum of Ln(Sum of Area Burned t-13 to t-24) to Ln(Sum of Area Burned t-49 to t-60)	-0.03	0.02	-1.46	0.14	
3 [a]	Ln(VPD_t)	8.25	0.98	8.46	0.00	2640
	Ln(Max T $^{o}K_t$)	-115.60	25.23	-4.58	0.00	
	Sum of Ln(Sum of Area Burned t-13 to t-24) to Ln(Sum of Area Burned t-49 to t-60)	0.01	0.04	0.25	0.80	
4 [a]	Ln(VPD_t)	9.10	1.86	4.88	0.00	2640
	Ln(Max T $^{o}K_t$)	-63.78	43.80	-1.46	0.15	
	Sum of Ln(Sum of Area Burned t-13 to t-24) to Ln(Sum of Area Burned t-49 to t-60)	-0.07	0.04	-1.95	0.05	
		-2.50	0.92	-2.71	0.01	
5 [a]	Ln(VPD_t)	9.06	1.91	4.73	0.00	2640
	Ln(Max T $^{o}K_t$)	-117.40	40.09	-2.93	0.00	
	Sum of Ln(Sum of Area Burned t-13 to t-24) to Ln(Sum of Area Burned t-49 to t-60)	-0.04	0.03	-1.52	0.13	

6 [a]	Ln(VPD_t)	4.26	1.89	2.26	0.02	2640
	Ln(Max T °K_t)	61.90	52.28	1.18	0.24	
	Sum of Ln(Sum of Area Burned t-13 to t-24) to Ln(Sum of Area Burned t-49 to t-60)	-0.06	0.04	-1.55	0.12	
8 [a]	Ln(VPD_t)	8.05	0.86	9.37	0.00	2640
	Ln(Max T °K_t)	-120.64	13.19	-9.15	0.00	
	Sum of Ln(Sum of Area Burned t-13 to t-24) to Ln(Sum of Area Burned t-49 to t-60)	-0.08	0.04	-1.87	0.06	
9 [a]	Ln(VPD_t)	6.47	0.75	8.65	0.00	2640
	Ln(Max T °K_t)	-89.33	12.06	-7.40	0.00	
	Ln(Sum of Area Burned t-13 to t-24)	-0.11	0.13	-0.81	0.42	
	Ln(Sum of Area Burned t-25 to t-36)	-0.35	0.23	-1.54	0.12	
	Ln(Sum of Area Burned t-37 to t-48)	-0.44	0.10	-4.37	0.00	

[a] Parsimonious specification used in modeling.

Table C.4. USDA Forest Service National Forest Sum of the Square Root of Area Burned for All Fires Poisson Pseudo-Maximum Likelihood Equation Estimates, Monthly Data, January 1998 to December 2019. (Note: national forest indicator variable parameter estimates withheld to limit table size)

Region	Variable	Parameter Estimate	Standard Error	t-value	p-value	Observations
1	Ln(VPD_t)	7.56	0.85	8.86	0.00	2640
	Ln(Max T ^oK_t)	-82.81	18.33	-4.52	0.00	
	Ln(Sum of Area Burned t-13 to t-24)	0.01	0.02	0.58	0.56	
	Ln(Sum of Area Burned t-25 to t-36)	-0.06	0.03	-2.18	0.03	
	Ln(Sum of Area Burned t-37 to t-48)	0.04	0.03	1.76	0.08	
	Ln(Sum of Area Burned t-49 to t-60)	-0.03	0.02	-1.13	0.26	
2	Ln(VPD_t)	6.38	0.56	11.34	0.00	2640
	Ln(Max T ^oK_t)	-72.27	10.90	-6.63	0.00	
	Ln(Sum of Area Burned t-13 to t-24)	-0.01	0.02	-0.58	0.57	
	Ln(Sum of Area Burned t-25 to t-36)	-0.03	0.02	-1.55	0.12	
	Ln(Sum of Area Burned t-37 to t-48)	-0.03	0.02	-1.23	0.22	
	Ln(Sum of Area Burned t-49 to t-60)	-0.03	0.02	-1.36	0.17	
3	Ln(VPD_t)	3.03	0.27	11.10	0.00	2640
	Ln(Max T ^oK_t)	-7.12	6.26	-1.14	0.26	
	Ln(Sum of Area Burned t-13 to t-24)	0.03	0.02	1.54	0.12	

Region	Variable	Parameter Estimate	Standard Error	t-value	p-value	Observations
	Ln(Sum of Area Burned t-25 to t-36)	-0.02	0.02	-1.15	0.25	
	Ln(Sum of Area Burned t-37 to t-48)	0.01	0.02	0.46	0.65	
	Ln(Sum of Area Burned t-49 to t-60)	-0.01	0.02	-0.36	0.72	
4	Ln(VPD_t)	5.27	0.63	8.39	0.00	2640
	Ln(Max T ^oK_t)	-27.96	13.62	-2.05	0.04	
	Ln(Sum of Area Burned t-13 to t-24)	-0.03	0.02	-1.33	0.19	
	Ln(Sum of Area Burned t-25 to t-36)	-0.09	0.02	-4.03	0.00	
	Ln(Sum of Area Burned t-37 to t-48)	0.04	0.02	1.79	0.07	
	Ln(Sum of Area Burned t-49 to t-60)	-0.06	0.02	-2.46	0.01	
5	Ln(VPD_t)	3.92	0.70	5.60	0.00	2640
	Ln(Max T ^oK_t)	-28.01	15.26	-1.84	0.07	
	Ln(Sum of Area Burned t-13 to t-24)	0.01	0.03	0.38	0.71	
	Ln(Sum of Area Burned t-25 to t-36)	-0.01	0.02	-0.51	0.61	
	Ln(Sum of Area Burned t-37 to t-48)	-0.02	0.03	-0.91	0.36	
	Ln(Sum of Area Burned t-49 to t-60)	-0.02	0.02	-0.79	0.43	
6	Ln(VPD_t)	2.57	0.71	3.63	0.00	2640

Region	Variable	Parameter Estimate	Standard Error	t-value	p-value	Observations
	Ln(Max T ºK$_t$)	25.07	17.17	1.46	0.14	
	Ln(Sum of Area Burned t-13 to t-24)	-0.04	0.03	-1.62	0.11	
	Ln(Sum of Area Burned t-25 to t-36)	-0.02	0.02	-0.85	0.40	
	Ln(Sum of Area Burned t-37 to t-48)	-0.04	0.02	-1.79	0.07	
	Ln(Sum of Area Burned t-49 to t-60)	-0.06	0.03	-1.70	0.09	
8	Ln(VPD$_t$)	5.54	0.17	33.11	0.00	2640
	Ln(Max T ºK$_t$)	-88.23	2.79	-31.63	0.00	
	Ln(Sum of Area Burned t-13 to t-24)	0.00	0.02	0.05	0.96	
	Ln(Sum of Area Burned t-25 to t-36)	-0.02	0.02	-1.05	0.30	
	Ln(Sum of Area Burned t-37 to t-48)	-0.05	0.02	-2.36	0.02	
	Ln(Sum of Area Burned t-49 to t-60)	0.01	0.03	0.19	0.85	
9	Ln(VPD$_t$)	6.09	0.26	23.69	0.00	2640
	Ln(Max T ºK$_t$)	-106.94	4.63	-23.10	0.00	
	Ln(Sum of Area Burned t-13 to t-24)	-0.05	0.03	-1.63	0.10	
	Ln(Sum of Area Burned t-25 to t-36)	-0.09	0.03	-3.11	0.00	
	Ln(Sum of Area Burned t-37 to t-48)	-0.09	0.03	-3.05	0.00	

Region	Variable	Parameter Estimate	Standard Error	t-value	p-value	Observations
	Ln(Sum of Area Burned t-49 to t-60)	0.06	0.04	1.42	0.16	
2 [a]	Ln(VPD_t)	6.40	0.57	11.19	0.00	2640
	Ln(Max T ^oK_t)	-72.52	11.04	-6.57	0.00	
	Sum of Ln(Sum of Area Burned t-13 to t-24) to Ln(Sum of Area Burned t-49 to t-60)	-0.03	0.01	-2.60	0.01	
3 [a]	Ln(VPD_t)	3.03	0.27	11.08	0.00	2640
	Ln(Max T ^oK_t)	-7.15	6.26	-1.14	0.25	
	Ln(Sum of Area Burned t-13 to t-24)	0.03	0.02	1.59	0.11	
	Ln(Sum of Area Burned t-25 to t-36)	-0.02	0.02	-1.08	0.28	
5 [a]	Ln(VPD_t)	3.89	0.70	5.54	0.00	2640
	Ln(Max T ^oK_t)	-27.60	15.30	-1.80	0.07	
	Ln(Sum of Area Burned t-13 to t-24)	0.01	0.03	0.47	0.64	
	Ln(Sum of Area Burned t-25 to t-36)	-0.01	0.02	-0.48	0.63	
	Ln(Sum of Area Burned t-37 to t-48)	-0.02	0.03	-0.89	0.37	
8 [a]	Ln(VPD_t)	5.54	0.17	32.79	0.00	2640
	Ln(Max T ^oK_t)	-88.27	2.82	-31.32	0.00	
	Ln(Sum of Area Burned t-13 to t-24)	0.00	0.02	0.02	0.98	

Region	Variable	Parameter Estimate	Standard Error	t-value	p-value	Observations
	Ln(Sum of Area Burned t-25 to t-36)	-0.02	0.02	-1.03	0.30	
	Ln(Sum of Area Burned t-37 to t-48)	-0.05	0.02	-2.34	0.02	
9 [a]	Ln(VPD_t)	6.07	0.26	23.66	0.00	2640
	Ln(Max T ^oK_t)	-106.67	4.64	-22.98	0.00	
	Ln(Sum of Area Burned t-13 to t-24)	-0.06	0.03	-1.88	0.06	
	Ln(Sum of Area Burned t-25 to t-36)	-0.10	0.03	-3.16	0.00	
	Ln(Sum of Area Burned t-37 to t-48)	-0.09	0.03	-3.02	0.00	

[a] Parsimonious specification used in modeling.

Table C.5. Department of the Interior and USDA Forest Service Suppression Expenditure Two-Staged Least Squares Equation Estimates, Monthly Data, November 2012 to December 2019.

	Variable	Parameter Estimate	Standard Error	t-value	p-value	Observations
Office of Wildland Fire	Sum of Area $Burned_t^{0.5}$	-3.90	1.43	-2.72	0.01	87
	Sum of Area $Burned_{t-1}^{0.5}$	13.86	1.30	10.65	0.00	
	Constant	-3,745	4,410	-0.85	0.40	
Bureau of Indian Affairs	Sum of Area $Burned_t^{0.5}$	2,874	1,506	1.91	0.06	87
	Sum of Area $Burned_{t-1}^{0.5}$	1,525	1,064	1.43	0.16	
	Constant	3,138,045	1,072,132	2.93	0.00	
Bureau of Indian Affairs	Sum of Area $Burned_t^{0.5}$	1,144	857	1.33	0.19	87
	Sum of Area $Burned_{t-1}^{0.5}$	10,055	798	12.59	0.00	
	Constant	11,800,000	1,792,488	6.60	0.00	
Fish and Wildlife Service	Sum of Area $Burned_t^{0.5}$	-1,567	1,756	-0.89	0.38	87
	Sum of Area $Burned_{t-1}^{0.5}$	6,290	1,210	5.20	0.00	
	Constant	690,844	366,255	1.89	0.06	
National Park Service	Sum of Area $Burned_t^{0.5}$	2,712	6,970	0.39	0.70	87
	Sum of Area $Burned_{t-1}^{0.5}$	29,132	5,100	5.71	0.00	
	Constant	178,714	1,393,435	0.13	0.90	

Table C.6. USDA Forest Service Suppression Expenditure Two-Staged Least Squares Equation Estimates, Monthly Data, November 2004 to December 2019.

	Variable	Parameter Estimate	Standard Error	t-value	p-value	Observations
Region 1	Sum of Area $Burned_t^{0.5}$	10,640	1,484	7.17	0.00	182
	Sum of Area $Burned_{t-1}^{0.5}$	17,916	1,285	13.95	0.00	
	Constant	736,070	889,968	0.83	0.41	
Region 2	Sum of Area $Burned_t^{0.5}$	17,570	3,698	4.75	0.00	182
	Sum of Area $Burned_{t-1}^{0.5}$	24,127	2,772	8.70	0.00	
	Constant	-990,227	495,339	-2.00	0.05	
Region 3	Sum of Area $Burned_t^{0.5}$	15,670	4,246	3.69	0.00	182
	Sum of Area $Burned_{t-1}^{0.5}$	25,031	3,057	8.19	0.00	
	Constant	-2,350,851	1,444,538	-1.63	0.11	
Region 4	Sum of Area $Burned_t^{0.5}$	12,040	1,765	6.82	0.00	182
	Sum of Area $Burned_{t-1}^{0.5}$	25,417	1,472	17.27	0.00	
	Constant	380,312	764,039	0.50	0.62	
Region 5	Sum of Area $Burned_t^{0.5}$	26,529	5,647	4.70	0.00	182
	Sum of Area $Burned_{t-1}^{0.5}$	60,636	4,247	14.28	0.00	
	Constant	5,988,457	3,282,787	1.82	0.07	
Region 6	Sum of Area $Burned_t^{0.5}$	36,906	5,365	6.88	0.00	182
	Sum of Area $Burned_{t-1}^{0.5}$	27,263	4,174	6.53	0.00	

	Constant	1,012,362	2,028,979	0.50	0.62	
Region 8	Sum of Area $Burned_t^{0.5}$	-13,505	3,841	-3.52	0.00	182
	Sum of Area $Burned_{t-1}^{0.5}$	24,367	3,616	6.74	0.00	
	Constant	1,485,648	1,297,634	1.14	0.25	
Region 9	Sum of Area $Burned_t^{0.5}$	684	1,826	0.37	0.71	182
	Sum of Area $Burned_{t-1}^{0.5}$	7,230	1,531	4.72	0.00	
	Constant	532,185	219,059	2.43	0.02	
Rest of Forest Service	Sum of Area $Burned_t^{0.5}$	26,352	6,463	4.08	0.00	182
	Sum of Area $Burned_{t-1}^{0.5}$	44,774	5,665	7.90	0.00	
	Constant	21,700,000	14,100,000	1.54	0.13	

Table C.7. Area Burned by Forest Service and Department of the Interior, Historical and Projected by Climate Scenario to FY 2099 (Monte Carlo Averages and Medians).

	GCM Label	GCM	RCP	Fiscal Year 2013-2019	2041-2059	2081-2099	2013-2019	2041-2059	2081-2099
				Average Annual Area Burned (Million Acres)			Median Annual Area Burned (Million Acres)		
Forest Service	Wet	cnrm_cm5	4.5	1.61	2.26	3.96	1.57	1.83	2.90
Forest Service	Hot	hadgem2_es365	4.5	1.57	4.45	7.92	1.51	3.97	6.75
Forest Service	Dry	ipsl_cm5a_mr	4.5	1.29	2.90	2.71	1.15	2.41	2.39
Forest Service	Least Warm	mri_cgcm3	4.5	1.05	1.37	1.44	1.00	1.31	1.41
Forest Service	Middle	noresm1_m	4.5	1.35	2.55	3.09	1.38	2.36	2.97
Forest Service	Wet	cnrm_cm5	8.5	1.29	3.24	12.80	1.26	2.80	8.30
Forest Service	Hot	hadgem2_es365	8.5	1.66	5.86	42.14	1.62	5.23	36.11
Forest Service	Dry	ipsl_cm5a_mr	8.5	1.30	3.60	11.98	1.29	2.95	8.27
Forest Service	Least Warm	mri_cgcm3	8.5	0.93	1.32	2.70	0.89	1.29	2.50
Forest Service	Middle	noresm1_m	8.5	1.21	4.48	13.39	1.18	3.30	9.36
Forest Service	All	All	All	1.33	3.20	10.21	1.28	2.53	4.24
Forest Service	All	All	80% Lower Bound	1.15	2.40	5.30	0.77	1.11	1.30

	GCM Label	GCM	RCP	Fiscal Year 2013-2019	2041-2059	2081-2099	2013-2019	2041-2059	2081-2099
				Average Annual Area Burned (Million Acres)			Median Annual Area Burned (Million Acres)		
Forest Service	All	All	80% Upper Bound	1.57	4.49	21.33	2.09	7.21	31.46
Forest Service	All	All	90% Lower Bound	1.12	2.28	4.42	0.66	0.93	0.84
Forest Service	All	All	90% Upper Bound	1.70	5.42	31.95	2.57	10.44	66.56
Forest Service	Historical	Average (FY2013-2019)		1.56					
DOI	Wet	cnrm_cm5	4.5	3.00	3.81	5.37	3.14	3.45	5.23
DOI	Hot	hadgem2_es365	4.5	3.02	6.03	8.85	3.04	5.61	8.64
DOI	Dry	ipsl_cm5a_mr	4.5	2.69	5.43	4.99	2.63	4.61	4.54
DOI	Least Warm	mri_cgcm3	4.5	2.18	2.93	3.29	2.10	2.76	3.16
DOI	Middle	noresm1_m	4.5	2.54	4.52	5.23	2.60	4.27	5.13
DOI	Wet	cnrm_cm5	8.5	2.40	4.90	10.38	2.32	4.72	9.95
DOI	Hot	hadgem2_es365	8.5	3.05	7.34	24.45	3.06	7.02	24.13
DOI	Dry	ipsl_cm5a_mr	8.5	2.74	6.64	15.67	2.64	5.56	13.82

	GCM Label	GCM	RCP	Fiscal Year 2013-2019	2041-2059	2081-2099	2013-2019	2041-2059	2081-2099
				Average Annual Area Burned (Million Acres)			Median Annual Area Burned (Million Acres)		
DOI	Least Warm	mri_cgcm3	8.5	2.13	3.01	5.83	2.08	3.00	5.65
DOI	Middle	noresm1_m	8.5	2.74	6.18	12.82	2.78	6.04	10.94
DOI	All	All	All	2.65	5.08	9.69	2.63	4.65	7.13
DOI	All	All	80% Lower Bound	2.35	4.30	7.58	1.78	2.55	3.24
DOI	All	All	80% Upper Bound	2.98	6.19	13.20	3.58	8.43	21.37
DOI	All	All	90% Lower Bound	2.30	4.15	7.20	1.61	2.30	2.75
DOI	All	All	90% Upper Bound	3.09	6.53	14.70	3.88	10.21	28.48
DOI	Historical	Average (FY2013-2019)		2.20					
FS + DOI	Wet	cnrm_cm5	4.5	4.63	6.09	9.36	4.85	5.47	8.26
FS + DOI	Hot	hadgem2_es365	4.5	4.59	10.53	16.70	4.58	9.59	15.89
FS + DOI	Dry	ipsl_cm5a_mr	4.5	4.00	8.32	7.75	3.89	7.03	7.01
FS + DOI	Least Warm	mri_cgcm3	4.5	3.22	4.29	4.72	3.06	4.10	4.60

	GCM Label	GCM	RCP	Fiscal Year					
				2013-2019	2041-2059	2081-2099	2013-2019	2041-2059	2081-2099
				Average Annual Area Burned (Million Acres)			Median Annual Burned Area (Million Acres)		
FS + DOI	Middle	noresm1_m	4.5	3.88	7.10	8.34	4.14	6.84	8.49
FS + DOI	Wet	cnrm_cm5	8.5	3.70	8.15	23.37	3.60	7.58	18.86
FS + DOI	Hot	hadgem2_es365	8.5	4.73	13.31	66.71	4.67	12.46	63.17
FS + DOI	Dry	ipsl_cm5a_mr	8.5	4.02	10.34	28.13	3.90	8.47	22.70
FS + DOI	Least Warm	mri_cgcm3	8.5	3.05	4.32	8.50	2.93	4.30	8.33
FS + DOI	Middle	noresm1_m	8.5	3.94	10.66	26.61	4.01	9.41	20.71
FS + DOI	All	All	All	3.98	8.31	20.02	3.96	7.38	12.08
FS + DOI	All	All	80% Lower Bound	3.59	7.04	14.09	2.61	3.76	4.79
FS + DOI	All	All	80% Upper Bound	4.42	10.23	33.28	5.65	16.18	57.03
FS + DOI	All	All	90% Lower Bound	3.50	6.75	13.19	2.33	3.35	4.04
FS + DOI	All	All	90% Upper Bound	4.57	11.11	43.12	6.44	21.47	96.49
FS + DOI	Historical	Average (FY2013-2019)		3.77					

Table C.8. Suppression Expenditures (billions of constant 2022 dollars) by Forest Service and Department of the Interior, Historical and Projected by Climate Scenario to FY 2099 (Monte Carlo Averages and Medians).

	GCM Label	GCM	RCP	Fiscal Year 2013-2019	2041-2059	2081-2099	2013-2019	2041-2059	2081-2099
				Average Annual Expenditures (2022 Billion $)			Median Annual Expenditures (2022 Billion $)		
Forest Service	Wet	cnrm_cm5	4.5	2.87	3.40	4.29	2.91	3.32	4.15
Forest Service	Hot	hadgem2_es365	4.5	3.02	4.82	6.06	3.01	4.67	6.04
Forest Service	Dry	ipsl_cm5a_mr	4.5	2.71	3.96	3.93	2.68	3.70	3.78
Forest Service	Least Warm	mri_cgcm3	4.5	2.43	2.81	2.86	2.41	2.74	2.82
Forest Service	Middle	noresm1_m	4.5	2.69	3.81	4.27	2.62	3.69	4.33
Forest Service	Wet	cnrm_cm5	8.5	2.62	4.03	6.98	2.54	3.94	6.56
Forest Service	Hot	hadgem2_es365	8.5	3.17	5.84	13.14	3.06	5.70	12.91
Forest Service	Dry	ipsl_cm5a_mr	8.5	2.75	4.56	8.03	2.60	4.14	7.26
Forest Service	Least Warm	mri_cgcm3	8.5	2.32	2.76	3.96	2.28	2.72	3.79
Forest Service	Middle	noresm1_m	8.5	2.80	4.64	7.11	2.85	4.51	6.63
Forest Service	All	All	All	2.74	4.06	6.06	2.71	3.85	4.91
Forest Service	All	All	80% Lower Bound	2.60	3.78	5.43	2.16	2.58	2.81

	GCM Label	GCM	RCP	Fiscal Year 2013-2019	2041-2059	2081-2099	2013-2019	2041-2059	2081-2099
				Average Annual Expenditures (2022 Billion $)			Median Annual Expenditures (2022 Billion $)		
Forest Service	All	All	80% Upper Bound	2.89	4.38	7.14	3.39	5.93	11.29
Forest Service	All	All	90% Lower Bound	2.54	3.69	4.41	2.01	2.40	2.34
Forest Service	All	All	90% Upper Bound	2.96	4.51	7.40	3.58	6.59	13.68
Forest Service	Historical	Average (FY 2013-2019)		2.86					
DOI	Wet	cnrm_cm5	4.5	0.60	0.68	0.79	0.62	0.67	0.80
DOI	Hot	hadgem2_es365	4.5	0.61	0.84	0.99	0.61	0.82	1.01
DOI	Dry	ipsl_cm5a_mr	4.5	0.58	0.80	0.80	0.58	0.77	0.78
DOI	Least Warm	mri_cgcm3	4.5	0.54	0.61	0.63	0.54	0.60	0.63
DOI	Middle	noresm1_m	4.5	0.57	0.75	0.80	0.56	0.73	0.80
DOI	Wet	cnrm_cm5	8.5	0.55	0.77	1.11	0.55	0.77	1.10
DOI	Hot	hadgem2_es365	8.5	0.62	0.93	1.78	0.62	0.92	1.75
DOI	Dry	ipsl_cm5a_mr	8.5	0.59	0.90	1.48	0.58	0.85	1.36
DOI	Least Warm	mri_cgcm3	8.5	0.54	0.62	0.84	0.54	0.62	0.83

	GCM Label	GCM	RCP	Fiscal Year 2013-2019	2041-2059	2081-2099	2013-2019	2041-2059	2081-2099
				Average Annual Expenditures (2022 Billion $)			Median Annual Expenditures (2022 Billion $)		
DOI	Middle	noresm1_m	8.5	0.60	0.85	1.20	0.61	0.85	1.16
DOI	All	All	All	0.58	0.77	1.04	0.58	0.76	0.92
DOI	All	All	80% Lower Bound	0.54	0.71	0.93	0.49	0.58	0.65
DOI	All	All	80% Upper Bound	0.62	0.84	1.14	0.67	0.98	1.62
DOI	All	All	90% Lower Bound	0.54	0.70	0.91	0.47	0.56	0.60
DOI	All	All	90% Upper Bound	0.63	0.84	1.14	0.69	1.07	1.89
DOI	Historical	Average (FY 2013-2019)		0.50					
FS + DOI	Wet	cnrm_cm5	4.5	3.47	4.09	5.08	3.54	4.00	4.96
FS + DOI	Hot	hadgem2_es365	4.5	3.63	5.65	7.04	3.60	5.50	7.05
FS + DOI	Dry	ipsl_cm5a_mr	4.5	3.30	4.75	4.72	3.27	4.44	4.55
FS + DOI	Least Warm	mri_cgcm3	4.5	2.98	3.41	3.50	2.95	3.33	3.43
FS + DOI	Middle	noresm1_m	4.5	3.26	4.56	5.08	3.19	4.39	5.15

	GCM Label	GCM	RCP	Fiscal Year 2013-2019	2041-2059	2081-2099	2013-2019	2041-2059	2081-2099
				Average Annual Expenditures (2022 Billion $)			Median Annual Expenditures (2022 Billion $)		
FS + DOI	Wet	cnrm_cm5	8.5	3.18	4.80	8.08	3.07	4.72	7.66
FS + DOI	Hot	hadgem2_es365	8.5	3.78	6.77	14.83	3.69	6.60	14.64
FS + DOI	Dry	ipsl_cm5a_mr	8.5	3.34	5.45	9.47	3.17	4.99	8.59
FS + DOI	Least Warm	mri_cgcm3	8.5	2.86	3.38	4.79	2.80	3.32	4.59
FS + DOI	Middle	noresm1_m	8.5	3.41	5.49	8.30	3.47	5.38	7.79
FS + DOI	All	All	All	3.32	4.83	7.09	3.30	4.62	5.81
FS + DOI	All	All	80% Lower Bound	3.17	4.56	6.48	2.67	3.16	3.45
FS + DOI	All	All	80% Upper Bound	3.48	5.16	8.21	4.04	6.88	12.97
FS + DOI	All	All	90% Lower Bound	3.12	4.49	5.48	2.50	2.96	2.91
FS + DOI	All	All	90% Upper Bound	3.54	5.19	8.30	4.24	7.67	15.46
FS + DOI	Historical	Average (FY 2013-2019)		3.35					

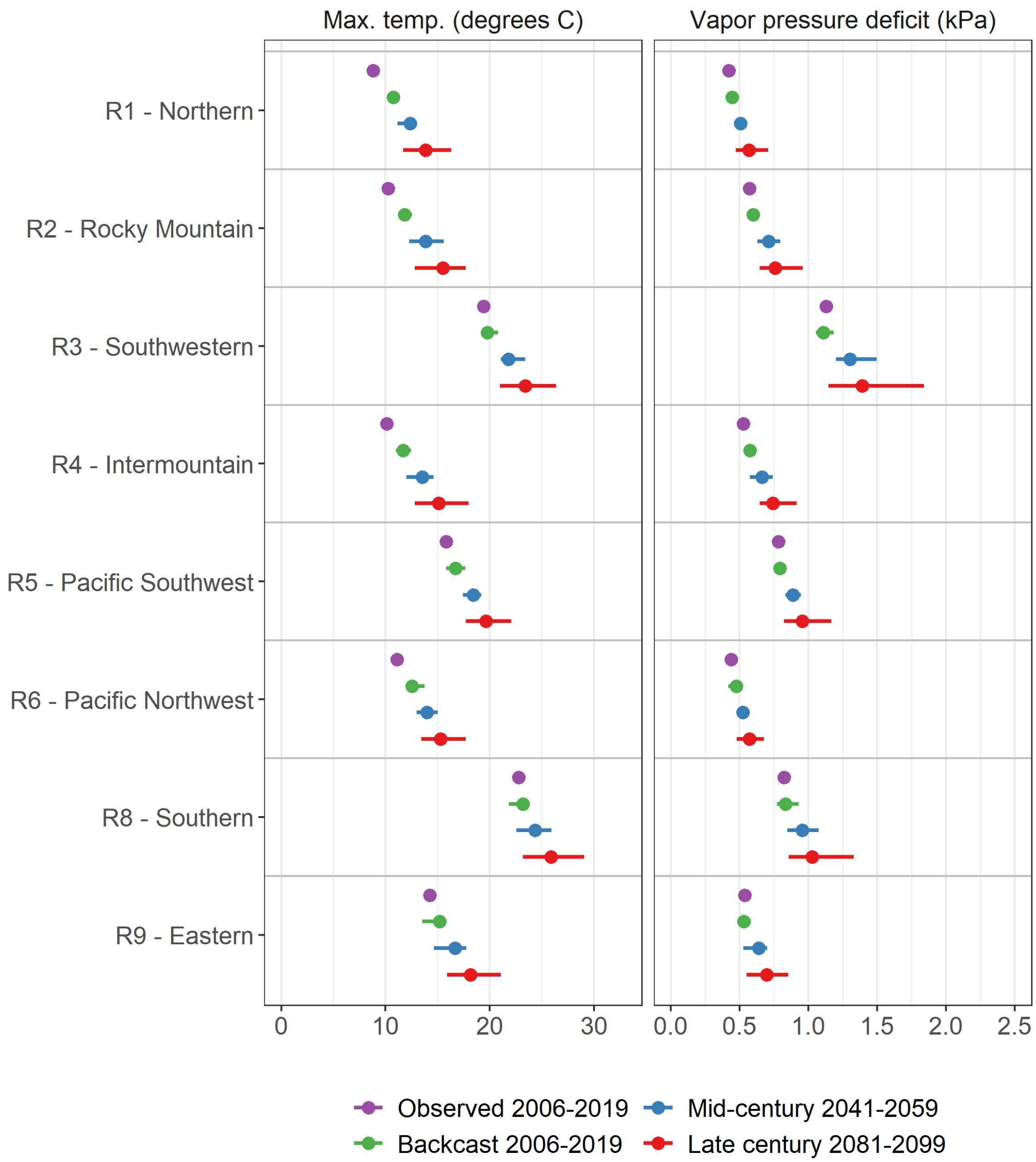


Figure C.1. Average (median) monthly maximum temperature and vapor pressure deficit by region on Forest Service lands for the historical observed period (2006-2019) and for the ten plausible futures (5 GCMs x 2 RCPs) used in the projections for the backcast (2006-2019), mid-century (2041-2059) and late century periods (2081-2099). In the backcast, mid-century, and late century periods, the point indicates the median of average values across all ten plausible futures, while the bars represent the range in average values across all futures. Both variables were used in regional models for FS area burned and square root of area burned.

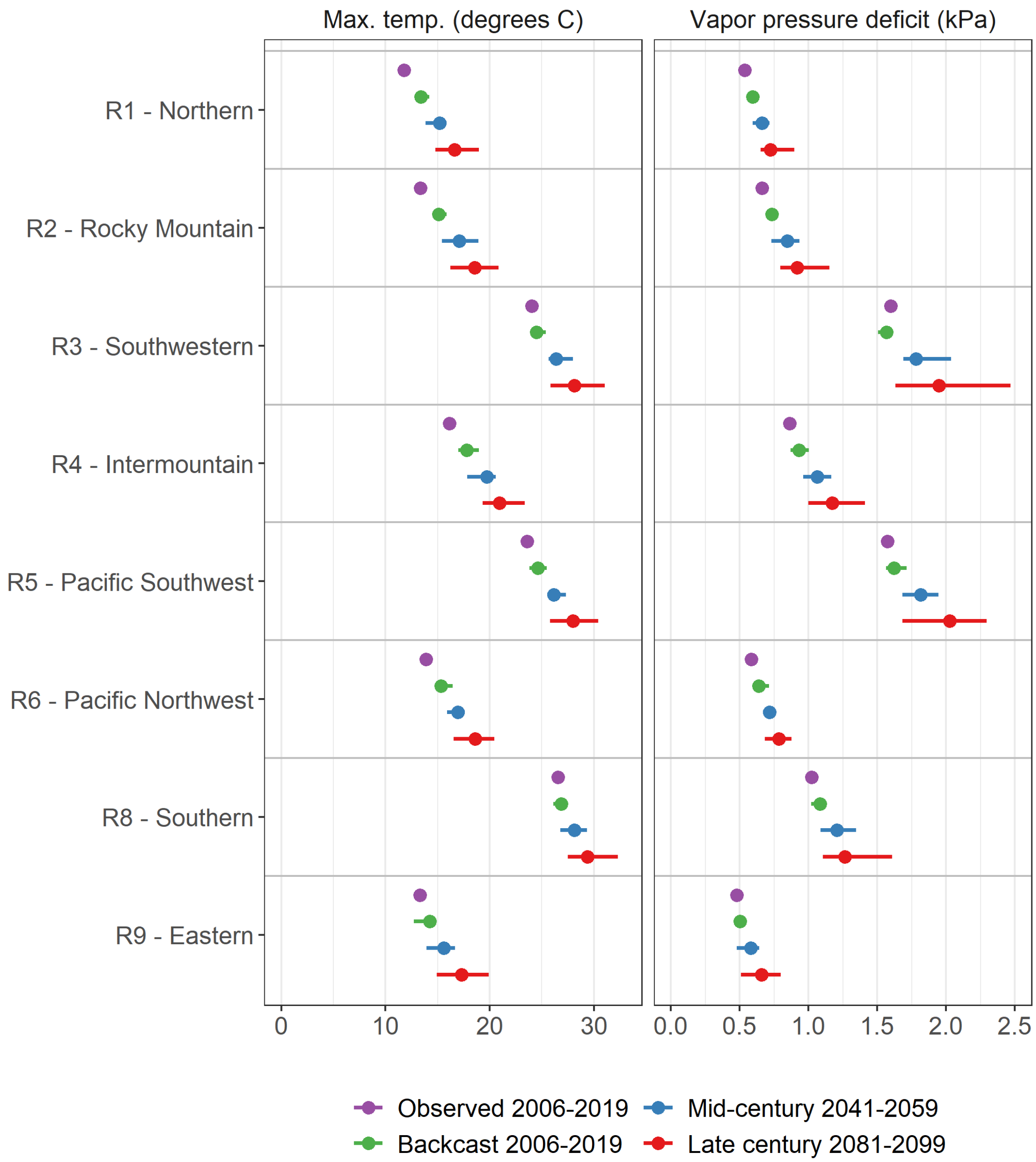


Figure C.2. Average (median) monthly maximum temperature and vapor pressure deficit by region on Department of the Interior lands for the historical observed period (2006-2019) and for the ten plausible futures (5 GCMs x 2 RCPs) used in the projections for the backcast (2006-2019), mid-century (2041-2059) and late century periods (2081-2099). In the backcast, mid-century, and late century periods, the point indicates the median of average values across all ten plausible futures, while the bars represent the range in average values across all futures. Both variables were used in models for area burned and the square root of area burned on DOI lands (with limited exceptions, for BLM lands in regions 2, 4, 5, and 6).

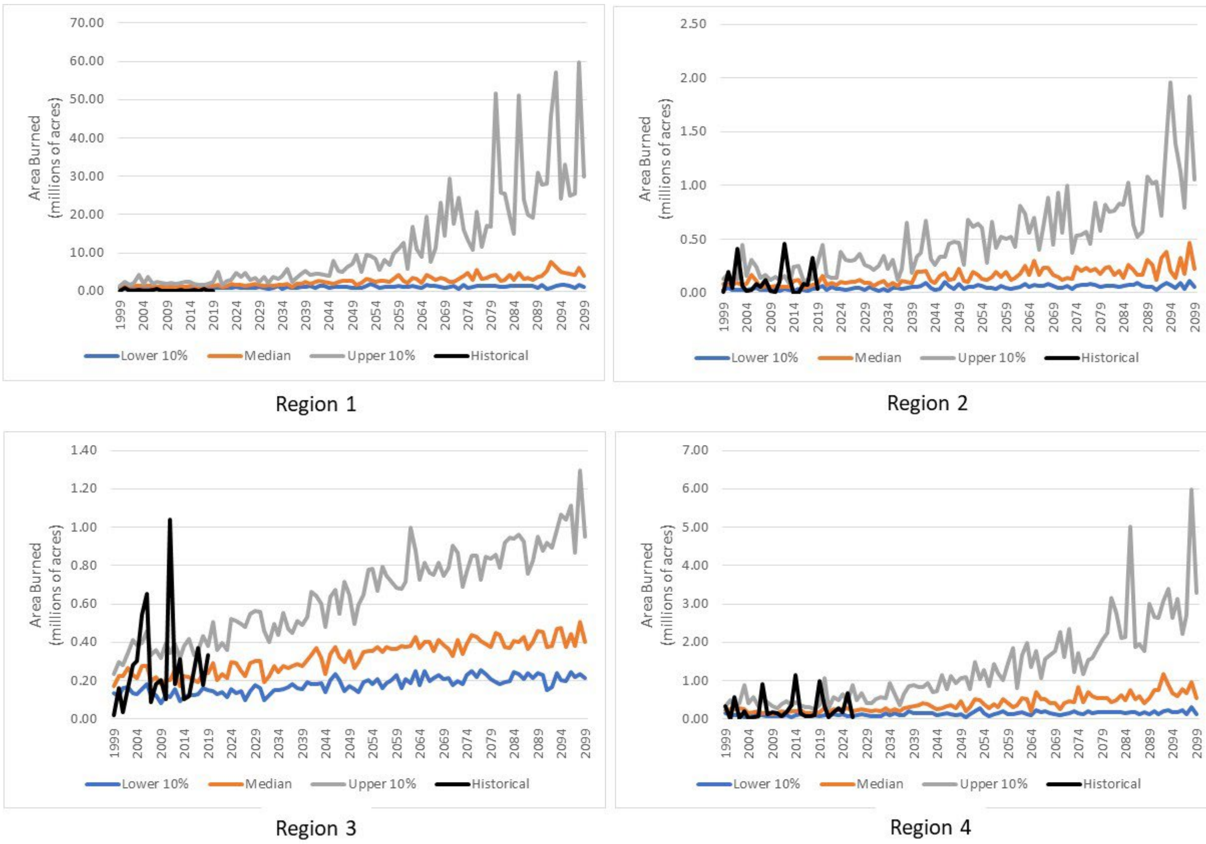


Figure C.3. USDA Forest Service regions 1-4 median and 80% upper and lower bounds of area burned projections, all climate projections combined. Monte Carlo 50 iterations per GCM x RCP scenario (i.e., 500 iterations included in this figure).

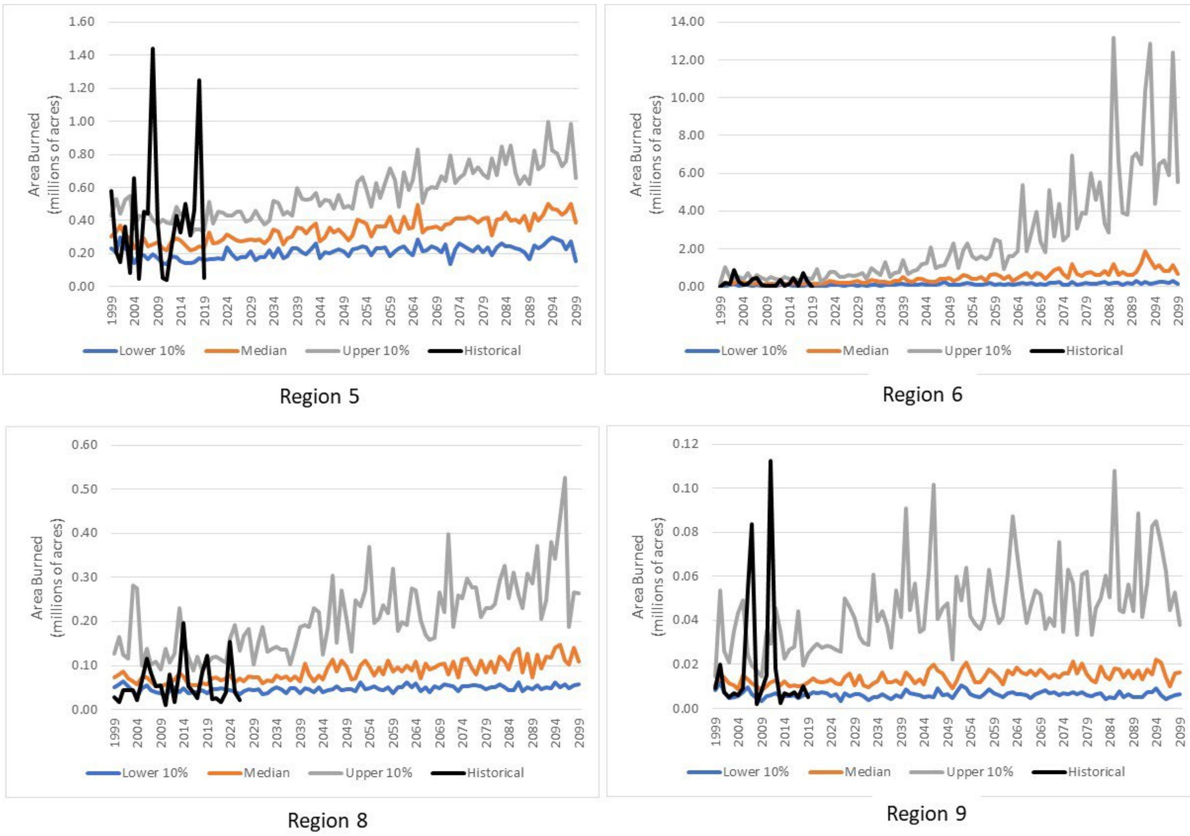
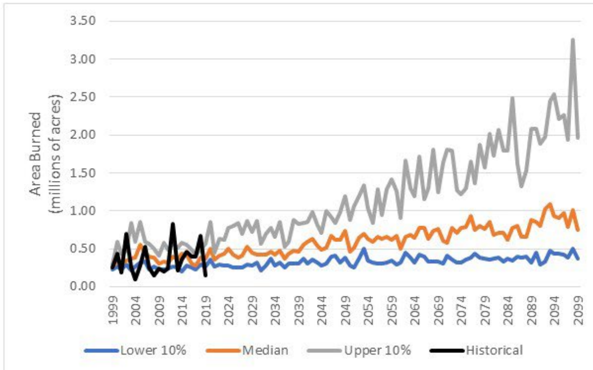


Figure C.4. USDA Forest Service regions 5-9 median and 80% upper and lower bounds of area burned projections, all climate projections combined. Monte Carlo 50 iterations per GCM x RCP scenario (i.e., 500 iterations included in this figure).



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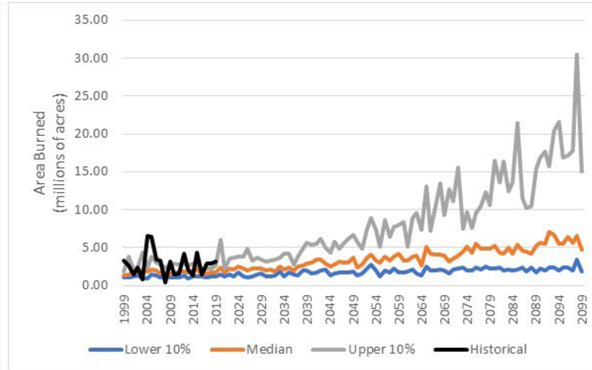
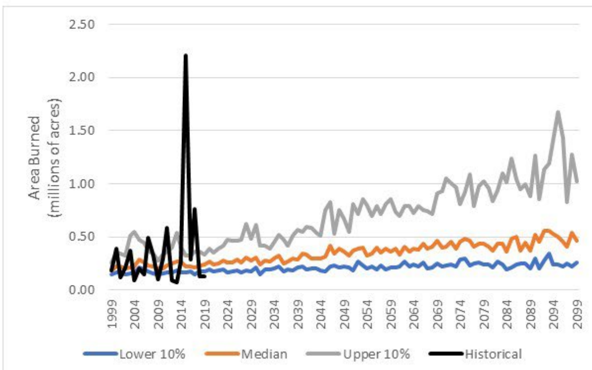
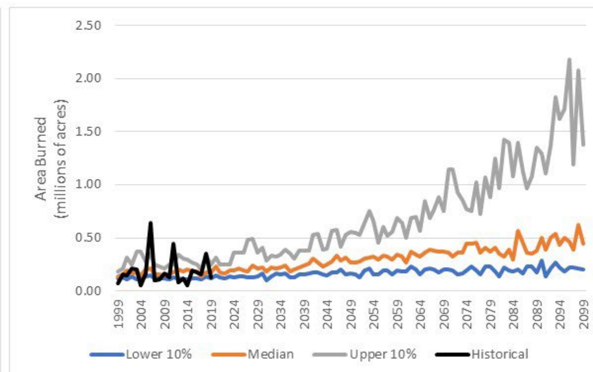


BLM



FWS



NPS

Figure C.5. Department of the Interior median and 80% upper and lower bounds of area burned projections four bureaus, all climate projections combined. Monte Carlo 50 iterations per GCM x RCP scenario (i.e., 500 iterations included in this figure).